A Dissertation

entitled

Should I Look for More or Not? Construction and Assessment of a

New Adaptive Information Search scale

by

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Submitted to the Graduate Faculty as partial fulfillment of the requirements for the

Doctor of Philosophy Degree in Psychology

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An Abstract of

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The current work proposes and tests a new adaptive information search scale (AISS) which assumes maximizing (prefer to look through all choices) and satisficing (satisfied with a good enough choice) are not unidimensional constructs and, can identify maximizers, satisficers and adapters.

Study 1 found the maximizing scale developed by Schwartz et al. (2002) could not predict the variability of information search as a function of choice complexity. In Study 2, the AISS scale was developed, refined and tested using item analysis and exploratory factor analysis. In Study 3, the scale was administered to a separate sample of 728 to test its constructive validity using CFA. Latent class analysis revealed 4 different classes: maximizers, satisficers, adaptive maximizers and adaptive satisficers. Also the subscales were tested for internal consistency and correlations with other variables. Finally, Study 4 tested whether AISS and MS can really predict changes in information search style as a function of choice complexity. Results indicated that AISS is a better predictor of change in information search style due to changes in choice complexity as compared to MS.

I dedicate this to my mother and father; who have always encouraged me to be myself and always move forward in life even when life is challenging.

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# Chapter 1

## Introduction

The everyday existence of modern man could be considered a continual series of decisions. Do I want salad, soup or a sandwich for lunch today?  Some of these choices are trivial or common occurrences and require only little deliberation and can be made quickly. Others are more momentous and require conscious and deliberate thoughts in order to determine the next course of action. For example, it would be expected that an individual faced with the choice of staying with his/her present job or accepting another would give careful consideration to gather information about each alternative and develop some sort of decision rule to evaluate his/her options and dictate a decision.

Developing a measure to document information search and information gathering is important for understanding and explaining everyday choice behavior. Similarly, descriptions of the strategies used during information search are important for understanding decision processes. Thus, a comprehensive tool to measure information search behavior would provide insight to individual differences in how information from the environment is gathered, organized, integrated and acted upon. Such a measurement tool is also invaluable from a practical standpoint. For example, health care providers could use prior knowledge of a person's search style to develop strategies to help people make thorough, rational decisions irrespective of their search style.  Marketing executives may also be able to better predict what kind of information search style will lead to what kind of search pattern and can organize their marketing campaign accordingly

## 1.1 Scales and Theories on Information Search for Decision Making

It has been established that environmental contexts and individual differences in information search affect our decision making abilities. However, rational choice theories including neo-classical economic theory and game theory do not take these into account. Instead, they propose that maximizing information search and selecting the best decision strategies yields the best outcome. Thus, everyone should follow that procedure. However, not all decision makers do not try to maximize information search and/or use best strategies to get the best quality decision. In practice, maximizing can be very laborious, taxing and sometimes improbable. Simon (1955, 1993) recognized this and proposed an alternative to the maximization objective. He suggested that actual decision makers might be more apt to try to find alternatives that are “good enough" rather than to try to find those that maximize their payoffs. He referred to this search pattern as satisficing.

Several years later Schwartz et al. (2002) developed a 13-item measurement tool called the maximizing scale that could help identify people with different search preferences. The scale identified people who prefer to maximize information search before making a decision, known as maximizers. It can also identify people who do not like to look for all possible information but only a few pieces that they think are important and are satisfied with a good enough option, they are known as satisficers. Schwartz et al. (2002) also added that for “satisficers,” extraneous options are not relevant once the satisficers’ primary needs have been met. However, who makes better decisions, maximizers or satisficers, has been the subject of inquiry in many studies over the past decade.

Nenkov, Morrin, Ward, Schwartz, and Hulland (2008) subsequently examined the factor structure of the maximization scale and found three factors, which they labeled as "alternative search," "decision difficulty" and "high standards." The "alternative search" category consisted of six items measuring the tendency to expend resources in exploring all possible opportunities (e.g., "When I watch TV, I channel surf, often scanning through the available options even while attempting to watch one program."). The "decision difficulty" category consisted of four items representing the degree of difficulty experienced when making choices among abundant options (e.g., "I often find it difficult to shop for a gift for a friend."). The "high standards" category consisted of three items reflecting decision makers' tendency to hold high standards for themselves and things in general (e.g., "No matter what I do, I have the highest standards for myself.")

Both the maximizing scale (Schwartz et al., 2002) and maximizing tendency scale (Diab, Gillespie, & Highhouse, 2008) propose that the construct of maximizing is unidimensional; that is, a person with maximizing tendencies consistently exhibit these tendencies across all decision situations. Similarly, a person with satisficing tendencies theoretically manifests satisficing tendencies consistently.

In contrast, Johnson ,Payne and Bettman (1988) in their adaptive decision making model suggested that in fact people are very adaptive in decision making and do not always follow similar rules for all situations. They proposed that a repertoire of different decision making strategies exists. One such strategy is described as compensatory decision making style. For example, the weight additive (WADD) model refers to a compensatory process that channels all relevant information and trades off the good and bad aspects of each alternative. Theoretically, this is always a better strategy as it ensures better quality decisions when properly used. However, it can be very exhaustive and non-parsimonious and thus sometimes unnecessary. There are other decision making strategies called heuristics, each leading to different levels of accuracy depending on task complexity and other factors. Some of these are non-compensatory; for example, elimination by aspects. Using a process-tracing technique that monitors information acquisition behaviors, Payne, Bettman and Johnson (1988) found that people use different kinds of heuristics during information search and are highly adaptive in their effort and accuracy tradeoffs which depend on situational demands.

The proposition of this theory is somewhat contrary to one of the fundamental aspects of the maximizing construct described by Schwartz et al (2002). In practice, based on adaptive decision making theory, it seems likely that maximizing and satisficing are not necessarily semantic opposites of a continuum. This is mostly because even though people have a predisposition about their choice and search performance, many of them make an effort and accuracy tradeoff on a case by case basis. Thus, the next section is devoted to forming an overview of the characteristics of maximizers and satisficers and providing a slightly different operational definition to these information search styles based on these characteristics.

## 1.2 Overall Characteristics and Operational Definition of Different Information Search Styles

### 1.2.1 Characteristics of Maximizers and Satisficers

Janis and Mann (1977) pointed out several of the distinct differences between the satisficing and maximizing strategies. With the satisficing strategy, information search is mostly incomplete; only a few dimensions need to be met for obtaining adequate results.

For each dimension the number of choice alternatives searched is also limited. The search concludes when a satisfactory option has been found. In contrast, maximizing strategy calls for a complete and exhaustive search where all attributes and alternatives are considered while making a decision. It is motivated by a desire to discover the best possible solution/option.

Another distinction between the maximizing and satisficing strategies is the type of information aggregation rule used to evaluate choice options. Simon's description of satisficing behavior implies that the decision maker is using a non-compensatory, multiple cut-off procedure to evaluate multidimensional alternatives. Thus the decision maker only requires that the alternative meets their minimum requirement on each aspect and is unconcerned with an excess on any dimension. An alternative which falls short on any dimension will be immediately discarded.

In contrast, the maximizers' information aggregation procedure could be characterized by a linear, compensatory combination model. Rather than discarding an alternative because it is low on one dimension, the decision maker will allow high scores on other dimensions to compensate for the deficiencies.

Although theoretically a maximizing information search should yield the best outcome, researchers suggest that in fact maximizers often demonstrate poor decision making quality. For example, according to Bruine de Bruin et al. (2007) and Parker, de Bruin, and Fischhoff (2007), maximizers themselves admit to making a greater number of poor decisions in their self -reported post-decision evaluations. The reason why maximizers sometimes make poorer decisions, (even though they are using the best strategy) could be because compensatory strategies such as weighted additive method are more complicated and thus difficult to follow. Moreover, he difficulty level increases with increase in choice complexity and leads to poorer performance when used without the help decision aids.

Several studies have attempted to explain the reasons behind overconfidence accompanied by poor performance in maximizers. Jain, Bearden and Filipowicz (2013) suggested that the difference in their prediction of their predictive ability and real predictive ability is due to the fact that maximizers give more noisy estimates; in other words, they do not follow a particular pattern during information search. Chowdhury, Ratneshwar, and Mohanty (2009) suggested that maximizers make poor decisions because they engage in more (and unnecessary) pre-choice browsing behavior, perceive more decision time pressure(Moderated by number of choices) and are very indecisive about their final choices. Polman (2010) suggested that maximizers, during their extensive search for alternatives, give undue weight to negative quality attributes; therefore, they end up making poorer choices. For example, Polman (2010) (using the Iowa gambling task) found that maximizers were more prone to alternate between decks and sample from more decks, which ultimately resulted in greater loss.

Not surprisingly, maximizers also tend to be unsatisfied with their choices. Schwartz et al. (2002) showed that maximization was negatively correlated with happiness, optimism, self-esteem, and life satisfaction and positively correlated with depression, regret, and perfectionism. Schwartz (2000) suggested that maximizers are unhappy for two reasons. First, they feel the need to look for all possible information and feel weighed down by it. Second, they always assume there could be an unforeseen alternative that could be better than what they chose, and it causes unanticipated regret.

Roets, Schwartz and Guan (2012) supported this idea by proposing that maximizers show greater regret in countries where choice is abundant; for example, the U.S. and Europe compared to non-Western societies. Schwartz et al. (2002) suggested that maximizers also feel regretful because of the improper use of upward social comparison.

Recent studies, however, argue that such condemned fate of maximizers could arise from the measurement scale devised to measure maximizing; it has limitations and it leads to faulty intensification of regret. Nenkov et al. (2008) used 2-item measures of each of the three factors. They found that scores on the high standards category were positively correlated with optimism, negatively correlated with depression, and uncorrelated with subjective happiness. Decision difficulty showed the opposite pattern, being negatively correlated with subjective happiness and optimism and positively correlated with depression. Lai (2010) concluded that the decision difficulty category is the key factor leading to negative correlations with well-being outcomes, which supports the findings of Nenkov et al. (2008). In contrast, Diab et al. (2008) found evidence suggesting that the high standards category was responsible for this relationship, because smaller correlations were found when maladaptive personality traits were compared to the Maximization Tendency Scale rather than the Maximization Scale. Rim, Turner, Betz, and Nygren (2011) proposed that only the alternative search and decisional difficulty factors are both positively correlated with each other and negatively correlated with well-being. High standards correlated strongly with the Maximization Tendency Scale (consisting of mainly high standards items) and were strongly correlated with positive indices of well-being (e.g., optimism and happiness) Thus, all these studies have suggested that maximization measures consist of several components and the method of measurement that was used highly influenced the relationship with well-being indices. However, the main reason for this inconsistency in the research could be because not all maximizers act the same way.

Comparatively fewer studies exist to understand the characteristics of Satisfiers. This line of research try to speculates why satisficers prefer fewer choices. One reason why satisficers prefer fewer choice factors because of cognitive limitations. Another reason is the need for cognitive closure. A study by Houghton (1998) suggested that individuals who have a high need for cognitive closure are less sensitive to missing information ("omissions"). This decreased sensitivity leads to more extreme, more confidently held judgments of a product described by an incomplete set of attributes. We know satisficers have greater need for cognitive closure (Amit & Sajiv, 2013) as compared to maximizers; thus, having to look through too much information gets in the way of achieving cognitive closure.

### 1.2.2 Characteristics of Adapters

There are at least two reasons that justify why sometimes it might be advisable to discontinue information search prematurely. First, sometimes due to situational demands, such as huge information load or time pressure, it is improbable for one to be able to evaluate all the options properly and consider their relative merits. Second, it might be redundant or unnecessary to engage in further search, especially, if a lot of effort is needed for further search and the potential outcome is only marginally better. Also sometimes, even if a far better option can be obtained with more searches, the decision situation could be so subjectively trivial to the decision maker that it would not be worth the effort. Maximizers, in theory, ignore all these justifications when they engage in extensive search behavior.

On the other hand, there are a few reasons for why someone should continue their search even if their initial criteria for a choice have been met. First, if with a little additional search, a much better choice can be found, it seems logical to put in that extra effort. It also makes sense to expend extra effort for decisions that have high subjective importance or long term consequences - for example, health decisions, finding a job, choosing a major or buying a house. One could argue then that satisficers despite such justifications stop their search prematurely.

A third category of decision makers seems to incorporate the best of both worlds; these are called adapters. Adapters consider all the pros and cons for both continuing search extensively and cutting it short prematurely. They conduct mental calculations to balance effort and outcome when engaging in information search; thus, adapters are successful in achieving optimal results.

Research evidence suggests that many decision makers combine maximizing and satisficing strategies and take a mid-way approach (Janis & Mann, 1977). For example, they may use a linear combination rule but exhibit incomplete search by ceasing to search alternatives before all possible options have been explored, thus using a suboptimal and less complex quasi-satisficing strategy. In another study, Wright (1974) showed that while choosing between information aggregation strategies for evaluating cars, the thought process used by 41% of all decision makers' aligned with a combinatorial model of maximizing and satisficing strategies. Another piece of confirming evidence are phased narrowing studies that involve multiple stage decision making; people in these studies tend to satisfice and look for less attributes in initial stages. However as their options get narrowed to fewer in number they tend to use more compensatory process to make their final decision (Levin & Jasper 1995). Finally, Glueck (1974) found that when job hunting, business students engaged in search patterns varying in degree of completeness showing that they were very adaptive in their search and did not always follow a preset rule of either maximizing or satisficing during their job hunt.

### 1.2.3 Operational Definitions of Different Information Search Style

In light of this evidence, the following operational definitions for maximizing satisficing and adapting are proposed.

**Maximizing is a particular cognitive style of information search where maximum effort is given to actively seek information for all possible choices for making a decision, with motives to find out the best possible choice, and thus, always giving more weight to accuracy while making accuracy- effort tradeoffs. It is also marked by post decision indecisiveness, especially when it is uncertain whether the best decision has been made.**

**Satisficing is a particular cognitive style of information search where a preformed criterion for decision making exists and information searchers are driven by need for closure to end the search as soon as the criteria are fulfilled, even if there is a possibility for a better choice than what has been chosen. Thus, satisficers give more weight to reducing effort and are ready to compromise with accuracy. Post decision indecisiveness is unlikely.**

**Adapting is a particular cognitive style of information search where a tradeoff between effort and accuracy is highlighted. Thus, decision accuracy is**

**crucial, and more given effort in information search is likely. But when finding the best choice is deemed unimportant or improbable due to some set constraints, unnecessary effort in information search is avoided.**

## 1.3 Factors Affecting Adaptive Information Search

Although the concept of adapting is well-known in the context of decision making theories, is not taken into account as an individual difference trait. Thus, it is important to delineate what factors make a person adapt and how adapting works.

### 1.3.1 Environmental Complexity

One crucial factor that makes people adapt accordingly is environmental complexity. A U-shaped curve has been proposed to describe the relationship between environmental complexity and the complexity of human information processing (Schroder, Driver, & Streufert, 1967). It is hypothesized that the most complex information processing and decision making behavior will occur at some optimal level of environmental complexity. At suboptimal or supra optimal levels information processing will be impaired.

Several variables may be important in determining the level of environmental complexity. Perhaps the most researched of these are uncertainty due to incomplete information and increased information load leading to choice complexity. For instance, Kida, Moreno, and Smith (2010), examined whether individuals' investment decisions are affected by choice-set size (i.e., a limited vs. extensive choice set) and found that the paradox of choice phenomenon does exist but only for participants who are less experienced with investing. They suggested that investors get more adaptive with time and can handle changes in choice set without affecting their decision quality. Nowlis, Dhar, and Simonson (2010) also suggested that consumers are adaptive and adjust their choice according to decision order. They showed that consumers choose more variety, when they consider a less replaceable attribute in an earlier, rather than a later, stage in the purchase decision. For example, consumers choose a greater quantity when flavor (or brand) decisions precede, rather than follow, size decisions.

Other evidence of adaptive decision making comes from studies using freedom of choice. Shanahan et al. (2010), using a computer simulation study, paired two out of three choice options (forced, partial, and complete freedom of choice) together and asked participants to choose one of the two options. They found that satisficers preferred forced choice over partial freedom or complete freedom of choice; maximizers preferred complete freedom of choice over partial or forced choice; and adapters preferred partial choice when paired with forced choice, partial choice when paired with complete choice, and complete choice when paired with forced choice, thus showing adaptive tendencies. Bearden and Connolly (in press) suggested that satisficers, when guided properly using a simplified sequential search problem, can act as optimal satisficers and can successfully choose the optimal choices.

### 1.3.2 Time Pressure

Another important factor that encourages people to become adaptive is time pressure. A number of real-world occupations deal with this realm on a regular basis, including air traffic controllers, sports players, and emergency service dispatchers. Thomson et al. (2008) used a signal detection task to find that nurses' decision making quality and strategies change with changes in time pressure, and this effect was mediated by nursing expertise. Specifically, when nurses gain expertise they become more adaptive. This helps them achieve better decision quality even under time pressure compared to non-experts who are not as adaptive. Macquet and Fleurance (2007) reported on a study involving naturalistic decision-making in expert badminton players taken under time-pressured conditions. In sum, these players performed successfully because they dynamically adapted to situations under time pressure. Hayes et al. (2012) suggested that people who are more adaptive make quick decisions and perform better in their “Traffic Light" task, which requires participants to take risks under time pressure. Betsch et al. (1999) suggested that under too much time pressure people cease being adaptive; instead, they cling to their pre-learned behavioral routine because being adaptive is strenuous under time pressure. Chowdhury, Ratneshwar, and Mohanty (2009) found that when maximizers are required to make quick purchase decisions, they feel a lot more time pressure and always choose to reconsider their selections made under time pressure (given an opportunity),

### 1.3.3 Metacognition for Information Search

Another factor that makes a person adaptive or nonadaptive is one’s metacognition about their cognitive abilities and its limits. It seems plausible that satisficers underestimate their cognitive abilities whereas maximizers overestimate their cognitive skills while adapters may be more accurate about their cognitive skills in comparison.

Reed, Mikels, and Lockenhoff (2012), in two studies, examined the role of perceived self-efficacy in decision making in preference for choice. They experimentally manipulated decision-making self-efficacy for an incentive-compatible choice among photo printers. Results showed that preferences for choice and pre-choice information seeking were significantly lower in a low-efficacy condition compared to a high-efficacy condition and a control group, suggesting that people's own perceptions about their ability influences their information search preferences. Kim, Shin, and Han (2014) examined how variations in the size of a consideration set can produce different affective consequences after making choices and investigated the underlying neural mechanism using functional Magnetic Resonance Imaging (fMRI). After rating their preferences for art posters, participants made a choice from a presented set and then reported on their level of satisfaction with their choice and the level of difficulty experienced in making their choice. Behavioral results demonstrated that despite real choice size, people's perception of choice difficulty as a function of choice plays a greater role in their choice set preferences. Another explanation for seeking or not seeking variety is drawn from implicit theory of personality about self. People who believe that personality as a trait is stable and constant and do not change over time are less prone to seek variety, whereas people who think that their personality is malleable and can be changed over time are linked to seek more variety (Hoyer & Ridgeway 1984). This gives another explanation for differences in metacognition of maximizers and satisficers. Finally, Shiloh, Koren, and Zakay (2001) found that compensatory decision-making style and need for closure influenced the subjective complexity of the decision task.

### 1.4 Further Evidence for Multidimensionality in Information Search

The construct of adaptiveness is based on the notion that people use different kinds of strategies and vary their information seeking preferences according to the situation, leading to the assumption that the same person can satisfice and maximize within the same situation. That is, these are not mutually exclusive behaviors. In the following section further empirical evidence will be provided about multidimensionality in information seeking processes.

Diab, Gillespie, and Highhouse (2008) argued that the multidimensional nature of the maximization scale was contradictory to the definition of maximizing tendency as, “a general tendency to pursue the identification of the optimal alternative” (p. 365; Diab et al., 2008). Previous studies (Linda, 2010; Nenkov, 2008) have suggested that maximization measures consist of several components, and that the relationships with well-being indices were heavily influenced by the method of measurement. In an attempt to clarify, the nature of the maximization construct and the degree to which its elements were related to measures of psychological well-being, the maximization scale and the maximization tendency scale were examined in four studies conducted by Rim, Turner, Betz, and Nygren (2011). Rim et al. (2011) concluded that the Maximization Scale measures three separate factors as postulated by its authors, but only the alternative search and decisional difficulty factors were positively correlated with each other, and that they were negatively correlated with indices of well-being. In another study Turner, Rim, Betz, and Nygren (2012) found that the satisficing construct is unidimensional by itself and is not assimilated by other maximization factors (e.g., decision difficulty or alternative search), suggesting that the satisficing dimension should instead be treated as a separate and independent construct.

Based on this and the previous empirical evidence, the present study proposes a new scale where maximizing and satisficing will be measured separately using two separate scales. In addition, it will contain items designed to measure maximizers, satisficers and, most importantly, adapters.

### 1.5 New Scale for Measuring Information Search Styles

The present study introduces and tests a new scale to assess search style. It is referred to as the adaptive information search scale (AISS). It has two subscales that are scored separately; together they will help identify maximizers, satisficers, and adapters. These subscales are known as adaptive maximizing scale and adaptive satisficing scale.

Four studies were conducted to develop and test the predictive ability of AISS. In Study 1 we tested the ability of the currently used maximizing scale, developed by Schwartz et al. (2002), to predict maximizers, satisficers and adapters. Using process tracing and post decision choice measures, maximizers, satisficers and adapters were identified. In addition, the relationship between the maximizing scale and the process tracing and post decision measures were tested.

In Study 2, item analysis and factor analyses were used to determine the best items (from a larger item pool) for each of the two scales. After selecting the best items for each scale using item analysis, an exploratory factor analysis was conducted for each scale separately. The resulting factor structure and the estimated parameter values from these analyses are reported.

In Study 3, we tested the psychometric properties of the new scale. We used confirmatory factor analysis and tested to see if we could find the same factor structure, we obtained in Study 2, on a different group of subjects. Then, we used latent class analysis to see how many classes AISS can identify. This was a critical analysis because one main purpose of this project is to develop a scale that can not only satisfy maximizers and satisficers, but also adapters. The scale was also tested for different reliability and validity measures.

Finally, in Study 4, we tested the predictive ability of the AISS that identified maximizers, satisficers and adapters by comparing it with another more experimental measure called mouse trace. Mouse trace is so designed that by using its different process tracing measures, it can identify maximizers, satisficers and adapters as well. We tested to what extent AISS could account for the variability in data produced by these process tracing measures from mouse trace. We also compared the predictive ability of the maximizing scale to account for variability in data as well, this provided us with an opportunity to evaluate the scope of both these scale in measuring information search behavior.

## 1.6 Importance of Understanding Information Search and Implications of the New Scales

Information search is one of the most important steps in decision making as it helps to strengthen decision quality. A measure that helps understand preexisting individual differences in people that influence their information search therefore, is a key to understanding their decision processes as well as potential success and failure in decision making. The proposed scale will help identify not only the people with maximizing and satisficing tendencies, but also people who are more adaptive to the situation. In doing so, the AISS should increase the predictive abilities of researchers in information search and decision making.

The scale may also help to understand real decision makers in various situations, such as, job satisfaction (Giacopelli et al., 2013), partner search (Schwartz 2002), managerial decision making (Peng 2013), health decision making and consumer decision making to name a few.

# Chapter 2

## Scale Measurement and Testing

Four studies were conducted over a period of two years to develop and test the new AISS scale. Each of these studies with results and analysis are described below.

### 2.1 Study 1

The purpose of the first study was to investigate whether the maximizing scale developed by Schwartz et al. (2002) can identify maximizers, satisficers, as well as, adapters.

For this purpose, we used a computerized process tracing measure called Mouse Trace that was designed by Levin and Jasper (1995) based on adaptive decision making theory. This software can record information search behavior and help analyze it using a variety of process tracing measures. These measures combined with different levels of choice complexity could identify maximizing, satisficing and adapting tendencies in people while they are engaged in a hypothetical information search during decision making.

Three different levels of choice complexity were presented to each participant namely, 12, 24 and 48 pieces of information. Since each participant was presented with all three levels of choice complexity, the decision scenarios changed with each level of complexity. The scenarios included choosing a house, a used car, or a health insurance. Thus, for choice size 12, we used any one of the three decision scenarios (e.g., house) each of which had four options (house 1, house 2, house 3 or house 4). Each of the 4 options could be evaluated based on three different attributes which included rent, area and number of bedrooms. Please note that participants got only one of the three scenarios for the size 12 matrixes. Subsequently, participants were given a size 24 matrix with a different scenario (e.g., a used car) that had 4 options with 6 attributes to evaluate each option. Finally, they were given a 48 size matrix for the last of the three scenarios (e.g., health insurance) with 4 options that could be evaluated based on 12 attributes (See Table 1.1a-1.1c for a fuller description of those information matrices.)

### 2.1.1 Dependent Measures Used

We used different process tracing measures from the Mouse Trace software and some post decision questionnaires to understand participants' information search style. Each of these measures is described below.

#### 2.1.1.1 Process Tracing Measures

The primary process tracing measures used in this study are described below. This includes measures for the proportion of total boxes opened, average number of information pieces acquired and average open box time for each information.

Proportion of total boxes opened was calculated by dividing total number of boxes opened by total number of boxes available. Thus, for any level of choice complexity the greatest possible score for portion of total boxes opened is 1 (12/12, 24/24/, 48/48). All participants had to open at least one box before they could select an alternative. Thus, for choice size 12, if only one out of 12 boxes was opened, then its' lowest score would be 1/12. For choice size 24, the lowest possible score was 1/24, (if only one out of 24 boxes was opened). Similarly, if only one out of 48 boxes was opened, then its' lowest possible score was 1/48.

The average number of information pieces acquired was obtained by dividing total number of acquisitions made by total number of boxes. Note that total number of information acquisition is different from total number of boxes opened. For instance, in choice size 24, if a participant only opened 3 boxes, his/her score for proportion of boxes opened was 3/24. However, suppose the participant opened the first two boxes 3 times each and the last box 5 times. Thus, the total number of information obtained is calculated by adding the number of times each of the boxes was opened. In this case, the boxes were opened a total of 11 times, making the average number of information pieces acquired for choice size 24 to be 11/24. Note that of average number of information piece acquired can be less than 1, equal to 1, or more than 1. Average open box time was calculated by dividing total open box time for all the boxes by the number of boxes opened.

#### 2.1.1.2 Post Decisions Measures

Post decision measures included post choice decisions and satisfaction with the information and final choice. Specifically, participants were asked:

1. After they made the selections "Would you like to go back and look again? Yes or No
2. Would you prefer more choice, less choice, or no change in amount of information?

   1=less choice, 2= no change, 3= more choice
3. How satisfied are you with the given amount of information? where: 1=very dissatisfied to 5=very satisfied

4. How satisfied are you with your final choice? where: 1=very satisfied to 5=very dissatisfied

#### 2.1.1.3 Maximizing Scale

Maximization Scale (MS). MS (Schwartz et al., 2002) is composed of thirteen items that are designed to measure an individual's tendency toward making optimal decisions. The items are rated on a 7-point response scale with response options ranging from completely disagree (1) to completely agree (7). Higher scores indicate a greater tendency toward maximizing. (See Appendix B.2).

### 2.1.2 Hypotheses

The first hypothesis for this study was that for each of the following dependent measures described above, all participants will show different search patterns for different levels of choice complexities. They will engage in extensive search for low level choice complexity but comparatively shallow search as the complexity of choice increases. We also predicted that the maximizers will engage in a relatively more in depth search process as compared to satisficers. The third and final hypothesis was that there will be an interaction effect of choice complexity and maximizing tendency. Maximizers will consistently search more in depth across all levels of complexity; and satisficers will consistently exhibit limited search behavior in comparison across all the different levels of complexity. However, the adapters will look for more information and spend more time for a smaller choice size (12) but their depth of search will decrease with increase in choice complexity.

### 2.1.3 Method

The method used for Study 1 is described below.

### 2.1.3.1 Participants

The participant pool in this study consisted of 75 undergraduate students from the University of Toledo. Of the 75 undergraduate students, 39 were males and 36 were females. Also, the average age of the students was 19.5 years.

### 2.1.3.2 Procedure

Once the participants arrived to the lab, they filled out an informed consent form and answered a few demographic questions. After completion of the demographic questionnaire, Participants were presented with the mouse trace task, where they were assigned to all three levels of choice complexity: 12, 24 and 48. For each condition, they got one of the three scenarios: house, car or health insurance. They were instructed to go through the attributes and then choose one option they preferred out of the four given options. After making a selection, they were asked if they were are satisfied with their final choice or whether they would like to look again. After completing this task, the participants were given post decision questions described above.  Finally, they completed the maximizing scale (Schwartz et al., 2002).

### 2.1.4 Results

We conducted a repeated measures analysis variance to examine the within group effect of choice complexity. One way analysis of variance was conducted to examine the main effect of maximizing and mixed factor analysis of variance was conducted to analyze the interaction effect of levels of complexity and maximizing. The results for all dependent measures are presented below.

### 2.1.4.1 Multivariate Analysis

All th**e** indices for multivariate analysis are reported in Table 2.1. We found a main effect of level of choice complexity on all dependent measures, Wilk's lambda=.370, $F$ (12, 61) =8.65 $p$ <.01. There was no effect of maximizing score on the combined dependent measures at a multivariate level. Similarly, there was no interaction effect of choice complexity and maximizing score on the dependent measures at a multivariate level.

**2.1.4.2 Main Effect of Choice Complexity**

Our first hypothesis on main effect of choice complexity was confirmed. As the level of complexity increased the proportion of boxes opened decreased significantly, Wilk's lambda=.681, $F$ (2, 73) =17.11,$p$ <.01.The average acquisition of information also decreased with increase in complexity. However, the difference was not significant. Participants preferred to go back look again after making a final selection for lower levels of complexity. As the level of complexity increased participants desire to look again decreased significantly, Wilk's lambda=0.919, $F$ (2, 72) =3.18, $p$=0.047. Similarly, participants were more satisfied with the given amount of information at the lower level of complexity, and their satisfaction with the amount of information decreased with increases in complexity of choice. Participants significantly preferred more information ($M$=2.14) when level of complexity was low; they preferred no change in amount of information for medium level of choice complexity ($M$=2.08); and less amount of information for a high level of complexity ($M$=1.85), Wilk's lambda=.849, $F$ (2, 72) =6.378, p=.003.

**2.1.4.3 Main Effect of Maximizing**

Maximizing tendency is a continuous variable. In order to conduct the one way ANOVA, we first found the median value for maximizing tendency (Median=3.87). Using a median split we dichotomized the variable into maximizers (*N*=35) and satisficers (*N*=39). We used this dichotomized category for further analysis. We found a main effect of maximizing for 3 out of 7 dependent measures. Maximizers opened significantly higher proportion of boxes as compared to satisficers, $F$ (1, 74) =15.56, $p$<.01. They also preferred to look again after making a final choice significantly more than satisficers. $F$ (1, 74) =13.10, $p$<.01.Similarly, maximizers prefer significantly more information as compared to satisficers, F (1, 72) =5.08, p=.027. For the rest of the dependent measures, we did not find a significant difference between maximizers and satisficers (see Table 2.3)

#### 2.1.4.4 Interaction Effect of Maximizing and Choice Complexity

There was a significant interaction effect of level of choice complexity and maximizing tendency for average acquisition of information $F$ (2, 72) =4.3, $p$=016. Satisficers had a relatively lower average acquisition for lower and medium levels of complexity but increased with greater levels of complexity. Maximizers' average acquisition was greater than satisficers for all levels of complexity. Interestingly, maximizer's average acquisition was relatively greater for both low and high level of choice complexity as compared to the medium level of choice complexity. There was no significant interaction effect for any other dependent measures. The implications of these results are elaborated in the discussion section.

### 2.1.5 Discussion

It is evident from the process tracing measures of Mouse Trace as well as post decision measures that not all people consistently maximize or always satisfice but rather vary in their information search according to choice complexity. Study 1 suggested that although the maximization scale is effective in identifying maximizers, and satisficers, it is not sensitive to identifying adapters. That could be one of the reasons why we did not see an interaction effect between choice complexity and maximizing. Thus it seems necessary to develop and test an information search scale that can identify all 3 groups successfully. Hence the remaining studies are dedicated to development and testing of such a measure.

## 2.2 Study 2

The purpose of Study 2 was to develop an adaptive information search scale consisting of 2 subscales that measure adaptive maximizing and adaptive satisficing separately. A large item set containing 64 questions was constructed (see Appendix B.1). Thirty two items were added for each subscale. Three of the questions used in the present scale were taken from the maximizing scale proposed by Schwartz et al., (2002). Another two questions were taken from maximizing tendency scale constructed by Diab (2008). Another 4 items were taken from a decision making inventory by Nenkov (2008). The remaining items were constructed by the experimenter of this study based on the operational definitions used in this study for maximizers, satisficers and adapters. The best items were then selected based on exploratory factor analysis (EFA) and item analysis with Cronbach's alpha for deleted items. For the final scale a total of 32 items were retained, 16 item for each subscale. Each subscale had two latent factors, namely pre decision and post decision for adaptive maximizing scale and pre decision and post decision for adaptive satisficing scale. The method and results for this study are discussed below.

### 2.2.1 Method

#### 2.2.1.1 Participants and Data

A total of 435 participants participated in this study of undergraduate students at the University of Toledo. They received extra credit for their participation.

There were missing values for 22 participants; 10 had very few items answered so they were eliminated from the study. Remaining 425 undergraduate students' data was used for the study. Then the missing data were tested to make sure that they were missing at random and then finally the maximum likelihood method was used to replace missing values.

#### 2.2.1.2 Procedure

Participants were given a brief introduction stating that they were going to participate in a survey looking at information search and decision making. The survey with 64 items was presented using an online survey created using the Psych data website. For each item, participants were instructed to respond on a continuum of a 7 point scale, where 1= completely disagree and 7= completely agree.

To analyze the data, an EFA was conducted separately on both subscales using maximum likelihood extraction method with promax rotation. The number of latent factors that should be retained were selected based on the Eigenvalue>1 rule, and chi-square difference tests.

### 2.2.2 Results

To develop the two subscales, an EFA for each subscale was performed on the data set consisting of 425 participants' responses. Since we did not know how many latent factors were appropriate for this model, we conducted an exploratory factor analysis. The strategy was to purify the item pool iteratively. EFA suggested which items to remove on the basis of factory loadings on pattern Matrix. The first EFA was on 64 items. Based on chi square differences, the items were assigned to 5 factors for the maximizing subscale and 4 factors for the satisficing subscale. However, using factor loadings it was clear that several items did not provide large enough loadings (as they were below .4) onto any single factor, or they provided cross loadings on to multiple factors. These items were eliminated due to lack of contribution to the scale. After these items were deleted, 45 items remained for the adaptive decision scale.

A second EFA was performed on the remaining 45 items using models ranging from two to four factors. To fit these models, maximum likelihood extraction with a promax oblique rotation was used one more time. This time a 4 factor model fit best for maximizing scale and a 3 factor model fit best for satisficing scale. Again, several items did not provide large enough loadings (highest loading below .4) onto a single factor; they provided cross loadings on to multiple factors. These were deleted leaving 38 items for both subscales combined. The mean and standard deviation for each item was computed. The item total score and the Cronbach's alpha were also computed for each scale. These additional items were removed which improved the Cronbach's alpha and thus increased internal consistency of the scale.

Another EFA was performed. This time each subscale had 2 factors each and no other item was required to be dropped. Based on Eigenvalues (Adaptive maximizing 3.14, 2.50, 1.05), the Adaptive Maximizing subscale seemed to have 3 latent factors; however, the chi square difference test suggested a two factors were sufficient as the chi square difference between the 2 factor model and 3 factor model was not significant for the adaptive satisficing subs scale thus the final accepted model had two factors. For Adaptive satisficing subscale, the Eigenvalues for two factors were 4.17, 2.12. The chi square difference test results also suggested a 2 factor model fit. The two factors for the adaptive maximizing scales were named pre-decision -1 and post-decision -1 factor in maximizing. The two factors for the adaptive satisficing scales were named as pre decision -2 and post decision- 2 factors in satisficing (Table 2.7, 2.8). The item correlation and internal consistency for these items were high for each subscale and no further items were required to be removed. In fact, removing any item seemed to deteriorate Cronbach's alpha.

### 2.2.3 Discussion

With Study 2, using a series of EFAs and item analyses, we were able to develop an adaptive information search scale with two subscales, each of which had two factors. However, we still need to test the psychometric properties of the new scale. Hence another study is required for this purpose.

## 2.3 Study 3

The purposes of Study 3 were three fold. The first purpose was to conduct a confirmatory factor analysis to test its construct validity on a different sample. The second purpose was to conduct a latent class analysis to find out how many classes can this scale successfully identify. The third and final purpose of this study was to test the other reliability and validity measures for this scale.

### 2.3.1 Participants and Procedure

Study 3 had 730 participants from age 17-32 years. There were 19 missing values. Two participants had several missing values and their data was removed from the dataset. For rest 17 participants we estimated missing values with maximum likelihood procedures (i.e., the expectation maximization algorithm, using all available data to insert values into missing cells) using SPSS' Missing Value Analysis software (Schafer & Graham, 2002). The data collection used an online survey where participants were presented with different decision making scales and personality inventories.

### 2.3.2 Confirmatory Factor Analysis

In Study 2, we found that a 2 factor model fit best for adaptive maximizing scale and another 2 factor model fit best for satisficing scale. Since this was on a separate dataset , in Study 3 we used 6 separate confirmatory factor analyses using Mplus 7 to examine absolute model fit of the 6 models: the 2 subscales separately, for 1 factor and 2 factor, and the subscales put together for 1 factor and 2 factor . Model fit was evaluated using the Comparative Fit Index (CFI), Tucker Lewis Index (TLI), Akaike Information Criterion (AIC), Sample sized- adjusted Bayesian Information Criterion (BIC), Root Mean Square Error of Approximation (RMSEA), and Standardized Root MEAN Square Residual (SRMR) values. Model fit was determined using empirically-defined benchmarks, as follows: CFI and TLI >.95 indicative of excellent fit; RMSEA <.08 for adequate model fit; and SRMR <.05 for excellent fit (Hu & Bentler, 1999); and lower AIC and sample size adjusted BIC values. A 10-point BIC difference between models represents a 150:1 likelihood and “very strong” (po.05) support that the model with the smaller BIC value fits best (Kass and Raftery, 1995).

We also compared the 6 competing models using robust maximum likelihood estimation with the Satorra-bentler chi-square (S-B chi square) scaling correction, robust to non-normality (Satorra & Bentler, 2001). For the 2 factor model, AS items were specified to load on two separate factors. Factors were allowed to correlate, all error covariance were fixed to zero, and all tests were two tailed. S-B x square difference tests for nested models were used to compare the relative fit of the one -factor model to the 2 factor model separately for the AS scale, AM scale, and AISS scale (Fan & Sivo 2009). The different models, which are not nested, were compared on fit indices. A 10 point BIC difference between models represents a 150:1 likelihood and “very strong” ($p$<05) support that the model with the smaller BIC value fits best (Kass a& Raftery, 1995).

**2.3.2.1 Confirmatory Factor Analysis Results**

As shown in Table 2.9, all 6 competing models showed different levels of fit to AISS data, as evidenced by standard benchmarks (CFI and TLI >.95 and RMSEA <.08, and SRMR <.05). S-B chi square difference test revealed that compared to the 1 factor model, the 2 factor model had an excellent fit for AS subscale. For AM subscale compared to the 1 factor model, the 2 factor model had a good fit. For the combined scale neither 1 factor nor 2 factors seemed to be good fit as predicted.

S–B $\chi 2$ difference tests revealed that compared to the Model 1, Model 2 had a significantly better fit, for over scale $\Delta X^2(1)$ 18.64, $p$<.001; as did 2 factor model as compared to 1 factor model for AM subscale, $\Delta X^2(1) = 14.62$, $p$<.001; 2 factor model as compared to 1 factor model for As subscale $\Delta X^2(1) = 13.54$, $p<.001$. All three two-factor models showed a significantly better fit than the one-factor model.

### 2.3.3 Latent Class Analysis

In previous studies, only either exploratory and/or confirmatory factor analysis was conducted to evaluate the factor structure of existing maximizing scales. No study as yet has looked at how many classes the information search scale can identify using Latent Class analysis. In the present study, we hypothesized that the new adaptive information search scale would not only identify maximizers and satisficers but also adapters as a separate distinctive class.

Three different scales were used. The adaptive information search scale is a 32 item self-report measure of information search style scored on a 7 point scale. For validating classes situational dilemma measures developed by Diab, (2008) was used. This measure is comprised of number of situational dilemmas in which one has to make a choice. Appendix B.4 has all situational dilemma measures, below is one exemplar: Imagine you are at the car dealership and you have found a car that you really want at the right price, except that it is not in your ideal color. Getting the ideal color requires waiting a month for it to come into this dealership, or driving far away to another dealership and re-negotiating a deal.

a. You buy the car anyway because you need to buy a car soon.
b. You wait until the color that you want becomes available.
c. You go to more dealers to see if they have the color that you want.

Which behavior are you most likely to do?

Daily decisions asked about decisions taken in the past and information search behavior related to these decisions. There were 6 items for this scale, participants answered on 7 point scale from (0) strongly disagree to (6) strongly agree, to which extent they have problems with decisions in different life domains. One such item was: “It’s difficult for me to decide in the morning which clothes to wear.”

Analysis was conducted in 3 stages. The first stage involved the conduction of latent class analysis (MCLachan & Peel, 2000; Muthen, 2004), using maximum likelihood estimation with robust standard errors, to assess empirically based classes of respondents based on their adaptive information search total scores. With a sample size of 728, the study had an excess of the minimum sample size of 250 recommended by Nylund et al (2007) for the use of LCA. Latent class analysis estimated the fit of the class solution incrementally until no further significant benefits could be identified. A difference of 10 points on Bayesian information criteria (BIC) indicates a 150:1 likelihood that the model with the smaller BIC value is the substantially better fitting model (Raftery, 1995). Although a lower BIC indicates better fit, research has demonstrated that the Lo-Mendell-Rubin test is much more reliable in accurately detecting the number of classes (Nylund et al., 2007). Thus, the Lo-Mendell-Rubin test was used here to determine the optimal number of classes.

Using LCA we could identify to which of the 4 classes each participant belonged to, we used this information search class variable for the second and third stage analysis. The second stage involved an ANOVA that examined differences between the classes on questionnaires of information search scales.

The third stage used a MANOVA to compare the classes on situational dilemma and daily decisions measure

**2.3.3.1 Results for Latent Class Analysis**

A latent class analysis was conducted on the AISS scale. A 1 class model yielded a log likelihood of BIC= 7070.295. A 2 class model yielded a log likelihood of, BIC=5027.539, and entropy (denoting the overall proportion of correct class classification) =.994. A 3 class model yielded a log likelihood of BIC=1155.01, and entropy=.996. A 4 class model yielded a log likelihood of BIC=656.92, and entropy=.988, A 5 class model yielded a log likelihood of, BIC=564.992, and entropy=.972,

We found evidence that the 2 class solution was superior to a 1-class solution. Specifically, using the Lo-Mendell-Rubin adjusted likelihood ratio test (Lo,Mendell & Rubin , 2001), with empirical support for identifying a given model with K classes against a K-1 classes (Nylund et al 2007), the 2-class solution was superior , adjusted Lo-Mendell Rubin 2 LLdiff (8986.02), p<.01. The 3-class solution was superior to the 2 class solution, adjusted Lo-Mendell-Rubin 2 LL (diff (3985.22), p<.01. Finally, the 4-class solution was superior to the 3-class solution, adjusted Lo-Mendell-Rubin 2 LL (diff (2610.78) $p<.01$, with no solution greater than the 4 -class solution representing a better fit..

Stage two of the analysis sought to identify and describe the nature of the differences between the classes identified in the LCA on the AISS scale. The ANOVA on the AISS data was significant, $F$ (3,724) =27.813 p<.01. Mean, standard deviations, and results of LSD The LCA plot in Fig 2-1 identified that one class was consistent with maximizing (*N*=108), recorded scores on both AISS subscales in the higher range for maximizing and reverse satisficing score. A second class, consistent with the satisficing class (*N*=152), recorded lower scores on both AISS subscales in lower range for maximizing and reverse satisficing score. The two remaining classes appeared consistent with adapting, although largely differing in terms of extent of scale elevation. The third class-the adaptive maximizing was high on maximizing scale moderate of satisficing (*N*=214), the adaptive satisficing (*N*=254), was elevated on satisfying scale but low on maximizing scale. Posthoc LSD suggested that all classes were significantly different from each other.

To validate the AISS scale derived classes against two other measures of information search 2 indicators, a MANOVA was conducted to compare the 4 classes on the situational dilemma and daily decisions. The MANOVA was significant, $F$ (6, 711) = 69.82, $p < .001$.Means, standard deviations, and results of analyses for each scale can also be seen in Table 2.11. Using posthoc analysis we found that for daily decisions maximizers and adaptive maximizers were significantly different from rest 3 classes, adaptive satisficers were significantly different from maximizers and adaptive maximizers but not satisficers. For situational dilemma questions maximizers and satisficers were significantly different from all 3 classes. Adaptive maximizers differed from maximizers and satisficers but not adaptive satisficers. Adaptive satisficers differed from satisficers and maximizers.

Although we hypothesized that the adaptive information search scale should be able to identify 3 classes. Latent class analysis suggests that it can identify 4 classes. The

LCA plot and effect on other validating variables helped us understand how these 4 classes might differ from each other (see Table 2.11).

### 2.3.4 Measures for Testing Correlation

Study 3 examined the correlations of the two subscales with the criterion behaviors used in previous research. In previous studies (Linda, 2010; Nenkov 2008) there was contradiction about whether maximizing scale is negatively correlated with happiness and wellbeing and positively correlated with depression and regret. In this study, we looked at the correlation among each subscale as well as other measures. Below is a short description of the scales that were used. Coefficients alphas are presented in the main diagonal of Table 2.12.

Maximizing Tendency Scale (MTS). The MTS (Diab et al., 2008) is composed of nine items that are designed to measure an individual's tendency toward making optimal decisions. The items are rated on a 5-point response scale with options ranging from strongly disagree (1) to strongly agree (5). Higher scores indicate a greater tendency toward maximizing.

Maximization Scale (MS). MS (Schwartz et al., 2002) is composed of thirteen items that are designed to measure an individual's tendency toward making optimal decisions. The items are rated on a 7-point response scale with response options ranging from completely disagree (1) to completely agree (7). Higher scores indicate a greater tendency toward maximizing.

Indecisiveness. The indecisiveness scale (Frost & Shows, 1993) is composed of 15 items that are designed to measure compulsive indecisiveness. The items are rated on a 5-

point response scale with options ranging from strongly disagree (1) to strongly agree (5). Higher scores indicate greater levels of indecisiveness.

Avoidant Decision Making. The avoidant decision making measure (Scott & Bruce, 1995) is composed of five items that are designed to measure the extent to which an individual puts off making an important decision. The items are rated on a 5-point Likert–Type response scale with options ranging from strongly disagree (1) to strongly agree (5). Higher scores indicate greater levels of avoidance.

Regret. The Schwartz Regret Scale (Schwartz et al., 2002) is composed of five items that are designed to measure regret following a decision. The items are rated on a 7-point response scale with options ranging from completely disagree (1) to completely agree (7). Higher scores indicate greater levels of post–decision regret

Neuroticism. The Goldberg Neuroticism Scale (Goldberg et al., 2006) is composed of 20 items presented as short statements that would describe an individual as generally depressed, moody, doubt–filled, etc. Participants are asked to respond to each statement using a 5-point response scale ranging from strongly disagree (1) to strongly agree (5). Higher scores indicate greater levels of neuroticism

Life Satisfaction. The Satisfaction with Life Scale (Diener et al., 1985) is composed of five items that are designed to measure the extent to which an individual is satisfied with the current conditions in his or her life. The items are rated on a 5-point response scale with options ranging from strongly disagree (1) to strongly agree (5). Higher scores indicate higher levels of satisfaction.

Need for Cognition. The Need for Cognition Scale (Cacioppo et al., 1984) is composed of 18 items that are designed to measure the extent to which individuals enjoy engaging in effortful cognitive tasks. The items are rated on a 5-point response scale with options ranging from extremely uncharacteristic of you (not at all like you) (1) to extremely characteristic of you (very much like you) (5). Higher scores indicate greater

.

#### 2.3.4.1 Results for Correlation

Inter-correlations among all measures are provided in Table 2.12. Coefficients alphas are presented in the main diagonal. Some noticeable differences emerged between the adaptive information search scale, maximizing scale and maximizing tendency scale. First, AISS demonstrated substantially greater consistency in reliability. Coefficient alpha reliability for Adaptive Maximizing subscale was .8 for adaptive satisficing subscale was .77. The elimination of any item would decrease the internal consistency of the measure and the correlated item-total correlations range from .31 to .67.

Second, The Adaptive maximizing sub-scale showed stronger relationship with MTS and DMI and a moderate relationship with MS and need for cognition. Adaptive satisficing scale had lower correlation with MTS a need for cognition and negative correlation with MS, and a moderate correlation with DMI. The MS correlated positively with indecisiveness, avoidance, regret and neuroticism and negatively with life satisfaction. Adaptive maximizing scale correlated with indecisiveness, and there was low correlation with regret. It did not correlate with avoidance, neuroticism or life satisfaction. Adaptive satisficing scale correlated negatively with indecision and regret but did not correlate with any other variable.

### 2.3.5 Discussion

Study 3 was a very important step in construction of the AISS. We established that using separate subscales each with 2 separate factors has the model best fit. We found out that using these two subscales, we can divide information search style into four classes, namely maximizing, satisficing, adaptive maximizing and adaptive satisficing. We tested the effect of the classes on daily decisions and situational dilemma and found that the 4 classes differ in information search and decision making. We also tested the correlation of the new scale with several other related scales.

Even though we standardized the scale in Study 3, we do not know if this scale could predict information search behavior based on choice complexity, as measured via a different task. Study 4 is designed to test the scope of AISS.

## 2.4 Study 4

Study 1 used software program called Mouse Trace to study information search behavior for different levels of complexity. The dependent measures from this design helped us identify experimentally, participants who prefer more information or less information consistently across different levels of choice complexity, as well as participants who change their information search style based on changes in levels of complexity. Since the Maximizing scale was a scale developed to measure information search style, we examined whether the maximizing scale can account for different types of information search. We found that it can account for people who are consistent but not for people who change according to situation, i.e. adapters. In Study 4 we tested the new AISS scale using the same Mouse Trace program that we used in Study 1 and used the same dependent measures to measure changes in information search style. We also compared AISS with MS to see how well each can predict the spread in data for different dependent measures used to measure maximizing, satisficing and adaptive tendencies.

Since many undergraduate students usually have to go through the process of apartment search, we created a decision scenario where people needed to choose between different rental apartments. We compared decision processes, decision quality for the final decision, and post decision satisfaction for apartments with 4 attributes and 4 apartment options (choice size 16) and for apartments with 12 attributes and 4 apartment options (choice size 48). It should be noted that we did a pilot study on a separate sample to see what attributes they seem necessary while looking for apartment and how they would rank order them from most important attribute to least important attribute. We then chose the best 2 attributes and worst 2 attributes according to ranking for the 4 attribute condition. Likewise we chose the best 6 attributes and worst 6 attributes for 12 attributes condition. Also based on these attributes there was clearly a best choice for apartment out of 4 apartments, so we looked at whether there was a difference in decision quality for maximizers, satisficers, adaptive maximizers and adaptive satisficers overall and individually for choice size 16 and choice size 48.

### 2.4.1 Pilot Study

We conducted the pilot study mentioned above by generating 38 attributes that people might look at when searching to rent an apartment. We presented these to 74 participants and asked them to rank order them in ascending order. (see Table 2.13 for the list of attributes with ranks). We picked the best 6 attributes and worst 6 attributes based on participant ranking. We conducted a Wilcoxon signed- rank test to compare these 2 paired samples (best 6 attributes, worst 6 attributes) and found that they were significantly different from each other.  In sum we did this to counter the possible argument that participants looked at all attributes because all of the attributes were essential to make a decision. Also previous studies (Ratneshwar, & Mohanty 2009; Polman 2010) suggest that maximizers take into account all information including unimportant attributes while making a decision. We predicted that satisficers and adapters generally do not consider unimportant attributes, especially when a large number of choices are available. Thus, in order to discriminate maximizers from other groups we used best and worst ranked attributes for Study 4 and predicted that maximizers would look at even relatively unimportant information.

### 2.4.2 Process Tracing Measures

The Mouse trace software program was used to create an information matrix with two different choice complexities, through which participants could look through a variety of attributes and options select an apartment.

The process tracing and post decision choice measures used in Study 1 were used again. These measures were able to capture maximizing, satisficing and adaptive tendencies. Process tracing measures used were proportion of total boxes opened (total number of boxes opened /total number of boxes), average number of information acquisition (total number of acquisitions made/total number of boxes), and average open box time for each box.

#### 2.4.2.1 Post Decisions Measures

Post decision measures included post choice indecision and satisfaction with information and final choice. Specifically participants will be asked:

1. After they made the selections "Would you like to go back and look again?

Yes or No

2. Would you prefer more choices, less choices, or no Change in amount of information?

3. How satisfied are you with the given amount of information? where 1=very dissatisfied and 5=very satisfied

1. How satisfied are you with your final choice? where 1=very dissatisfied and 5=very satisfied

**2.4.3 Results and Analysis**

We conducted multivariate analysis of variance to evaluate the effect of information search style (measured by AISS,) and choice complexity on the process tracing and post decision measures. It was followed by multiple analysis of variance measures to analyze the main effect of choice complexity, and main effect of decision search style on all dependent measures. This was followed by analysis of the interaction effects of information search style and choice complexity on the dependent measures. We also conducted a series of regressions on each dependent variable and analyzed how much variability in dependent measures can be accounted for by the AISS above and beyond the maximizing scale overall as well as for different levels of choice complexity. Finally, we looked at how much variability in the dependent measures can be accounted for by maximizing scale above and beyond information search scale.

**2.4.3.1 Main Effect of Choice Complexity**

We conducted a Multivariate Analysis of Variance to analyze the effect of choice complexity (4, 12) with 4 (N=111) and 12 (N=98) attributes respectively on 7 dependent variables (Mentioned above in procedure section) combined. We found that there was an overall significant effect of choice size on all dependent variables combined F (7,187) =18.56 p<.01 Wilk's Lambda =0.590 (see Table 2.14).

The multivariate Analysis was then followed by several ANOVA to see how choice complexity affected each of the dependent variables separately. The descriptive statistics and results of F test with significance value for each of these ANOVA is shown in Table 2.15.

Participants opened significantly greater proportion of total available boxes(*M*=.87) for choice complexity 16 as compared to choice complexity 48(*M*=0.55), *F* (1,208) =61.36, *p*<.01. This means then when there were only 4 attributes available people were more likely to open 87% of the boxes as compared to when 12 attributes where available where on average they opened only 55% of the boxes.

Average acquisition also showed a similar pattern. People made more comparisons among different choices for choice size 16(*M*=1.39) as compared to choice size 48(*M*=.914), *F* (1,208) =57.56, *p*<.01. This shows that especially for the 4 attributes condition participants opened many of the boxes more than once since the mean is greater than 1. In comparison, for 12 attributes condition, they did not open it as many times.

Satisfaction with choice was measured on a 7 point scale where 1 indicated very satisfied and 7 indicated very dissatisfied. On average participants were more satisfied with their final choice (*M*=2.31) for 12 attribute as compared to 4 attributes (*M*=2.96), *F* (1,208) =10.98, *p*=0.008. This finding was opposite of what we hypothesized, as we predicted people would be more satisfied with their choice in the less attribute condition as compared to more attribute condition.

For choice preference people selected whether they wanted less information=(1), more information=(3) or no change =(2). On average participants preferred more information for 4 attribute condition (*M*=2.30) as compared to 12 attribute condition (*M*=1.79) $F$ (1,208) =37.51 $p$=0.01.

The rest of the dependent measures, average open box time, satisfaction with information and whether to go back for more after selection or not did not differ significantly for 4 attribute and 12 attribute conditions.

These results suggest that people search through information differently depending on amount of choice given to them and they are more through in their choice when they have to focus on fewer choices but less thorough when they have too many choices.

**2.4.3.2 Main Effect of Information Search Style**

The information search style measured by AISS is a continuous measure. We first used quartile scores to divide the measure into 4 groups. In Study 3, using LCA we found that the information search style scale identified 4 different classes/groups. So for Study 4 we wanted to compare 4 different groups, maximizers, satisficers, adaptive maximizers and adaptive satisficers. We conducted a multiple univariate analysis of variance to analyze the effect of information search styles (Maximizers *N*=52 adaptive maximizers *N*=58, adaptive satisficers *N*=47, and, Satisficers *N*=52) on the 7 dependent variables (Mentioned above in procedure section) combined. We found that there was an overall significant effect of information search styles on all dependent variables combined $F$ (21,567) =6.57, $p<.01$, Wilk's Lambda =0.519.

The multivariate analysis was then followed by several simple ANOVAs to see how different information search styles affected each of the dependent variables separately. The descriptive statistics and results of F test with significance value for each of these ANOVA has been shown in Table 2.16.

Maximizers looked at more information (1.47), followed by adaptive maximizers (1.31), and adaptive satisficers (1.06) satisficers (.772). This difference was significant $F$ (3,206)) =23.49 p <.001. Similar results were found for proportion open boxes as well. Maximizers opened greater proportion of open box(M=.881). This was followed by adaptive maximizers (.77), adaptive satisficers (.669) and finally satisficers (.534),the difference between the four groups was significant F (3,206) =35.68, p<.01. Satisficers were also most satisfied with their choice(M=1.98), and maximizers were least satisfied(M=3.58) with their choice whereas adaptive maximizers(M=2.47) and adaptive satisficers (2.52) slightly less satisfied than satisficers but more satisfied than maximizers, this difference was significant $F$ (3,206) =12.09, $p$=0.03. Maximizers were most likely to look for more information after making a choice (where, 1=yes, 0=no),(M=0.307) Adaptive maximizers also preferred to look for more choice(M=0.115). Satisficers(M=.012) and adaptive satisficers(M=.0004) preferred not look at more information after making a choice. These differences were significant, F (3,206) =.4.46 p=.005. Finally, Adaptive maximizers preferred no change in information(M=2.2) whereas adaptive satisficers(M=1.9) and satisficers(M=1.26) preferred less choices, F (3,206) =32.13.46 p<.01.

The average open box time and satisfaction was not significantly affected by information search style.

### 2.4.3.3 Main Effect of Maximizing Tendency

The maximizing tendency scale discriminates between maximizers and non-maximizers. Since we were conducting analysis of variance and this is a continuous variable, we calculated the median for maximizing tendency =3.86 and categorized the scale into maximizers for people above median and satisficers (non-maximizers) for people below the median split.

We found that there was an overall significant effect of maximizing tendency on all dependent variables combined *F* (21,187) =2.51, p<.01, Wilk's Lambda =0.017.
The multivariate analysis was then followed by several simple ANOVAs to see which how different levels of maximizing tendency affected each of the dependent variables separately. The descriptive statistics and results of F test with significance value for each of these ANOVA are shown in Table 2.17.

Maximizers acquired significantly more information (*M*=1.24) and had significantly greater proportion of open boxes (*M*=.744) compared to average acquisition of information by satisficers (*M*=1.03) and proportion of boxes opened by satisficers (*M*=.678), *F* (1,208) =7.69 *p*=.006 (average pieces of information acquired) and *F* (1,208) =4.93 *p*=.027 (proportion of boxes opened). Satisficers were significantly more satisfied with the given amount of information (*M*=2.52) and more satisfied with the choices they made (*M*=2.18) as compared to maximizers who were less satisfied with given amount of information (*M*=3.06) and were less satisfied with the choices they made (*M*=2.81), *F* (1,208) =4.33, *p*=.039 (satisfaction with given information) and *F* (1,208) =7.66 *p*=.006 (satisfaction with the final choice).

Differences in maximizing tendency did not significantly affect average open box time, whether look for more information again after making a choice, and choice preference.

**2.4.3.4 Interaction Effect of Information Search Style and Choice Complexity**

We found that there was a significant interaction effect of information search style and level of complexity on all dependent variables combined $F(21,567)=3.31$, $p<.01$, Wilk's Lambda =0.766

The multivariate analysis was then followed by several simple analyses of variance to assess the interaction of information search styles and choice complexities on each of the dependent variables separately. The descriptive statistics and Results of F test with significance value for each of these ANOVA has been shown in Table.2.17.

For 4 attribute condition adaptive maximizers had the greatest proportion of boxes opened ($M$=.967), followed by maximizers($M$=.972), and adaptive satisficers($M$=.852). Satisficers had the least proportion of boxes opened ($M$=.703) For 12 attribute condition, maximizers had a significantly greater proportion of boxes opened ($M$=.795) whereas the remaining 3 groups had relatively lower proportion of boxes opened for adaptive maximizers($M$=.576), adaptive satisficers($M$=.485), and satisficers($M$=.365) $F$ (3,201) =4.09 $p<.01$.

This is a very significant finding. It suggests that for less complex choices adaptive maximizers act like maximizers, who open a greater proportion of boxes. Even adaptive satisficers prefer opening greater proportion of boxes, unlike satisficers. However, when the level of choice complexity increases even though maximizers still prefer to open more proportion of boxes, adaptive maximizers, adaptive satisficers and satisficers open relatively lower proportion of boxes. This shift in information search style for both adaptive groups needs to be highlighted.

For 4 attribute condition ,satisficers are most satisfied with given amount of information(*M*=2.16) whereas maximizers are least satisfied (*M*=4.39). Adaptive satisficers(*M*=3.09) and adaptive maximizers(*M*=2.94) seem comparatively more satisfied than maximizers. For 12 attributes condition, interestingly, we see a reverse effect where adaptive satisficers are most satisfied with given amount of information(*M*=1.96) and satisficers are least satisfied(*M*=4.18). Adaptive maximizers(*M*=2.23) and maximizers(*M*=3.083) are relatively satisfied with the amount of information given $F$ (3,201) =11.95 p<.01.

Satisfaction with final choice also has interesting findings. Maximizers are least happy with their choice in both 4 attribute condition(*M*=4.5) and 12 attribute condition(*M*=2.66), whereas satisficers are most satisfied with their choice in 4 attribute condition(*M*=1.6) as compared to 12 attribute condition(*M*=2.37). Adaptive satisficers show the reverse effect in comparison to satisficers. They are more satisfied with their choice for 12 attribute condition(*M*=2.0) as compared to 4 attribute condition(*M*=2.95). Adaptive maximizers act very similar to adaptive satisficers and they are more satisfied with their choices for 12 attribute condition (*M*=2.23) when compared to 4 attribute condition(M=2.81), $F$ (3,201) =7.82 $p$<.01

Participants chose how much information they preferred on a 3 point scale, i.e. whether, they prefer less than given (1), same as what has been given (2) or more than what has been given (3). Satisficers consistently preferred less information in the 4 attribute condition(*M*=1.4) and even less information for 12 attribute condition($M$=1.22). Maximizers preferred more information in the 4 attribute condition ($M$=2.81) and no change in information the 12 attribute condition ($M$=2.41). Adaptive satisficers preferred more information for 4 attribute condition($M$=2.95) but less information for 12 attribute condition($M$=1.5). Adaptive maximizers, like adaptive maximizers, preferred more choice for both 4 attribute condition ($M$=2.78) and 12 attribute condition($M$=2.41).

**2.4.3.5 Interaction Effect of Maximizing Tendency and Choice Complexity**

There was no significant interaction effect of maximizing tendency and choice complexity for any of the seven dependent variables for Study 4.

**2.4.3.6 Regression Analyses Comparing AISS and MS**

Regression Analysis was conducted so that we could compare AISS and MS as continuous measures with different levels of complexity for each of the 7 dependent variables. Results of analysis for each dependent variable are presented as follows.

**2.4.3.6.1 Effect of AISS on Dependent Measures After Controlling for MS**

A two -stage hierarchical multiple regressions were conducted for each dependent variable, for categorical variables look for more or not a choice preference multiple logistic regressions was conducted. . The maximizing scale was entered first at stage one of the regression to control for effect of maximizing. The AISS was entered at stage two.

As you can see from Table 2.20 AISS significantly predicted variance in the following dependent measures after controlling for MS average acquisition, proportion of open box, satisfaction with choice, look for more on not and choice preference . However, it could not significantly account variance above and beyond MS for the following variables open box time, and satisfaction with given information. Overall, even after controlling for MS , AISS could significantly account for variation in a lot of dependent measures.

#### 2.4.3.6.1 Effect of M.S on Dependent Measures after Controlling for AISS

A two -stage hierarchical multiple regressions were conducted for each dependent variable, for categorical variables look for more or not a choice preference multiple logistic regressions was conducted. . The maximizing scale was entered first at stage one of the regression to control for effect of maximizing. The AISS was entered at stage two. As you can see from Table 2.21MS significantly predicted variance in the following dependent measures even after controlling for AISS average acquisition, look for more or not . However, it could not significantly account variance above and beyond MS for the following variables proportion of open boxes, open box time, and satisfaction with given information, satisfaction with given choice, choice preference. Even though MS did significantly predict variance in lot of dependent measures, after controlling for AISS , MS could only identify significantly very few of the dependent measures suggesting that AISS is better than MS in predicting information search.

#### 2.4.3.6.1 Interaction Effects of M.S , AISS and Choice Complexity on Dependent Measures after Controlling for all Main Effects

Since we were interested in interaction effect choice complexity and information search style, we also looked at interaction effects. All scores were converted to Z scores. A two -stage hierarchical multiple regressions were conducted for each dependent variable, for categorical variables look for more or not a choice preference multiple logistic regressions were conducted. . The main effects of MS, AISS and choice complexity was entered first at stage one of the regression to control for main effects of maximizing. The interaction terms were entered at stage two.

As you can see from Table 2.22, interaction effect of AISS and choice complexity significantly predicted variance in the following dependent measures even after controlling for main effects, average acquisition, proportion of open boxes, satisfaction with given information and satisfaction with final choice (see fig 2-2,2-3,2-4) .

Interaction effect of MS and choice complexity significantly predicted variance in only one dependent measure namely satisfaction with given information. It seems that even when used as a continuous scale AISS is better at predicting adaptive behavior as compared to MS. There was also a significant 3 way interaction for average acquisition and proportion of open boxes.

**Discussion**

Overall it seems important to note that although both AISS and MS could predict information search behavior based on different dependent measures. AISS could also predict differences in information search behavior caused by differences in choice complexity. MS on the other hand did not interact with choice complexity for any of the decision measures suggesting that AISS can identify adapters well.

## Chapter 3

## Overall Discussion

In this study we challenged the idea that maximizing versus satisficing is unidimensional which suggests that the same person is consistently maximizing information search or is a satisficer. Past studies have shown that people change strategies based on choice complexity. For example during a 2 or 3 stage phased narrowing task, in the initial stage where the complexity of choice is higher, people tend to choose some non-compensatory strategy, and may not look at all choices, use exclusion method to eliminate choices and so on. After narrowing down the options, the choice complexity is lower in the next phase, where people are more likely to look at more attributes and options and use a more compensatory strategy for choice. This clearly suggests that people do not always use the same strategy. The maximizing scale (Schwartz et al., 2002) is based on the assumptions that maximizing tendency in unidimensional in nature; thus the questions created by this measure are specifically targeted to distinguish between maximizers and non-maximizers. The problem with this approach is that it might not be able to account for the adaptive behavior of people which is very crucial for information search. In Study 1 we first showed that indeed people are adaptive and they use a different search style according to the complexity of choice. We also found that although maximizing scale can identify maximizers and satisfices it cannot identify people who are likely to change their information search style based on extraneous factors such as choice complexity. This suggested the need for a scale that can identify people who do not adapt to situations and are always either maximize or satisfice and people who do adapt to the situation, which we call adapters.

In Study 2 we generated items for the new information search style scale that had two separate subscales adaptive maximizing and adaptive satisficing. A few of these items were taken from the existing maximizing scale, maximizing tendency scale and decision making inventory the rest was new items. We conducted item analysis and exploratory factor analysis to eliminate any item that seemed redundant and non-contributive. We also found that each subscale had 2 latent factors; looking at how the items were clustered together we named them as pre decision and post decision items.

Study 3 was primarily conducted to determine the stability of the factor structure of this scale. It also used latent class analysis to measure how many different classes this scale can identify. This was a very crucial analysis as this could potentially tell us if adaptive information search scale can really identify adapters separately from maximizers and satisfices. We found that it can indeed identify adapters. It identified four different classes based on the pattern of answers. We named them as maximizers, satisfices, adaptive maximizers and adaptive satisfices. We also tested the scale for different other reliability and validity indices and found all of them to be satisfactory. In Study 4 we used Mouse Trace to identify maximizers, satisficers and adapters by using different process tracing measures as well as manipulating choice complexity. Then we analyzed how well the new adaptive information search scale and the old maximizing scale can account for variance in data in these dependent measures. We found that the adaptive information search style scale can account for greater variability in these dependent measures as compared to maximizing scale and can account for changes in information search behavior due to changes in choice complexity .Understanding information search style is a very crucial part of decision making. This scale can be extensively used for that purpose and can be used to predict people's information search style for making decisions.

Although the scale was used on 2 different samples, both of these samples were comprised of college students. It seems important totest this scale on the general population as well. In this study we used choice complexity to measure whether people adapt to changes in choice complexity in their information search. However, there are other situational factors that also impacts adaptability of information search; we need to test this scale for such other factors as few studies have looked at neurological correlates of adaptive decision making. Weller, Levin, Shiv and Becha (2007) looked at the neural correlates of adaptive decision making under risk using the adaptive decision making model. However, they did not classify people with different information search style. It seems important to classify people into different information search style and examine if neural correlates for decision making differ for these groups. In future we plan to study neural correlates of decision making for maximizers, satisficers, adaptive maximizers and adaptive satisficers.

Finally, there is a range of studies that explicitly describe the decision making behavior of maximizers, such as : maximizers are never satisfied with their choice, they sometimes look at negative /less important attributes, feel regret in their decisions and are more likely to engage in counterfactual thinking and so on. Satisficers are known to be more satisfied with their decision even if it is not the best choice, are less engaged in counterfactual thinking and use their past decisions to guide their present choices in similar situations. Not many studies have been to test the assumptions because to date all individuals were thought to be as either maximizer or satisficers. It is logical to assume that in many studies maximizers are not as unsatisfied and are not as poor decision makers as others because they were not just pure maximizers but also adaptive maximizers as well. Once we are able to draw these fine distinctions in information search we will be able to understand their decision making process and information search style and quality more adequately. This should potentially help predict their choices in a given situation with greater accuracy. It may also help us to better understand and predict decisions in more applied settings.

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**Appendix A**

**List of Tables and Figures**

Table 1.1.a: Attributes used for selecting house in Study 1

| House | Price | Area Sq Ft | # Beds | # Baths | Heat /AC | Pool | Style | Parking | additional outhouse | distance from hospital | garden in Sq Ft | Close to park |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 150,000 | 1000 | 2 | 1 | central | no | Palladian | open garage | yes | no | 500 | yes |
| 2 | 183,330 | 2000 | 3 | 2 | none | yes | Victorian | closed garage | no | no | 300 | no |
| 3 | 150,000 | 2500 | 3 | 1 | non-central | no | Tudor | street parking | no | yes | 800 | no |
| 4 | 350,000 | 3500 | 4 | 2 | central | no | Georgian | closed garage | yes | yes | 800 | no |

Table 1.1.b: Attributes used for selecting health insurance in Study 1

| Insurance | Maximum Limit | Deductible | Monthly payment | Maximum Out of Pocket | Prescription Covered | Dental Covered | in-network coinsurance after deductible | care network | vision covered | insurance paying emergency room visit | out of network coverage | insurance paying for annual health check up |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 50,000 | 400 | 350 | 6,300 | no | no | 20% | ppo | no | 100% | yes | 100% |
| 2 | 100,000 | 500 | 250 | 3,650 | yes | no | 10% | hmo | yes | 80% | no | 70% |
| 3 | 65,000 | 2000 | 50 | 1,200 | yes | yes | 15% | hmo | no | 80% | no | 80% |
| 4 | unlimited | 50 | 500 | 4850 | yes | yes | 0% | ppo | no | 100% | yes | 100% |

Table 1.1.c: Attributes used for selecting used car in Study 1

| Car | Price | Mileage | Odometer Reading | Make/model | Year | Previous Accidents | Color | engine cylinder | number of previous owner | GPS | type | drive mode |
|---|---|---|---|---|---|---|---|---|---|---|---|---|

| | | | | | | | | | s | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 9,000 | 35 | 50,000 | Toyota corolla | 2007 | none | silver | 2 | 2 | no | suv | manual |
| 2 | 5,000 | 28 | 80,000 | kia forte coupe | 2008 | front | black | 2 | 5 | yes | coup | auto |
| 3 | 2500 | 32 | 110,000 | ford fusion | 2001 | back | red | 2 | 3 | no | sedan | auto |
| 4 | 22,000 | 38 | 60,000 | BMW 3 series | 2014 | none | black | 4 | 1 | yes | sedan | auto |

Table. 2.1: Multivariate test for effect of choice complexity, maximizing score and interaction effect of choice complexity and maximizing on dependent measures combined for Study 1

| Effect | Wilk’s Lambda | F | Sig. |
|---|---|---|---|
| Main effect of maximizing | .921 | F(6,67)=.955 | .462 |
| Main effect of complexity | .370 | F(12,61)=8.655 | .000 |
| Interaction of maximizing And complexity | .768 | F(12,61)=1.535 | .136 |

Table 2.2 : Main effect of choice complexity on each dependent measure for Study 1

| Dependent Measures | Mean | | | Std. Error | | | Wilk's lambda | F test | P value |
|---|---|---|---|---|---|---|---|---|---|
| | 4 | 6 | 12 | 4 | 6 | 12 | | | |
| Proportion of open boxes | .875 | .790 | .690 | .027 | .029 | .027 | .681 | F(2,73)=17.13 | <.01 |
| Average acquisition | 1.400 | 1.329 | 1.482 | .055 | .052 | .104 | .944 | F(2,73)=2.151 | 0.124 |
| Average open box time | 1.002 | .953 | .962 | .046 | .060 | .044 | .983 | F(2,73)=.613 | .545 |
| Look again or not | .351 | .297 | .203 | .056 | .053 | .047 | .919 | F(2,72)=.3.182 | .047 |
| Satisfaction with information | 1.878 | 2.095 | 3.203 | .139 | .136 | .115 | .884 | F(2,72)=4.728 | .012 |
| Prefer more, less or no change | 2.149 | 2.081 | 1.865 | .063 | .074 | .073 | .849 | F(2,72)=6.378 | .003 |
| Satisfaction with choice | 2.054 | 1.932 | 1.716 | .132 | .114 | .108 | .916 | F(2,72)=3.283 | .043 |

Table 2. 3. Main effect of maximizing on each dependent measure for Study 1

| Dependent Measures | Mean | | Std. Error | | F test | P value |
|---|---|---|---|---|---|---|
| | Satisficers | Maximizers | Satisficers | Maximizers | | |
| Proportion of open boxes | .711 | .867 | .028 | .030 | F(1,74)=15.56 | <.01 |
| Average acquisition | 1.317 | 1.500 | .073 | .077 | F(1,73/0=2.29 | .140 |
| Average open box time | .965 | .980 | .041 | .044 | F(1,73)=.303 | .583 |
| Look again or not | .171 | .410 | .045 | .048 | F(1,72)=.13.10 | <.01 |
| Satisfaction with information | 2.325 | 2.467 | .127 | .134 | F(1,72)=.59 | .445 |
| Prefer more, less or no change | 1.923 | 2.152 | .070 | .074 | F(1,72)=5.085 | .027 |
| Satisfaction with choice | 1.778 | 2.038 | .128 | .135 | F(1,72)=1.96 | .166 |

Table 2. 4: Interaction effect of maximizing and choice complexity on each dependent measure for Study 1

| | 4 | | 6 | | 12 | | Wilk's Lambda | F test | P value |
|---|---|---|---|---|---|---|---|---|---|
| | S | M | S | M | S | M | | | |
| Proportion of open boxes | .810 | .947 | .708 | .881 | .616 | .773 | .994 | F(2,72)=.229 | .796 |
| Average acquisition | 1.237 | 1.581 | 1.270 | 1.394 | 1.444 | 1.524 | .892 | F(2,72)=4.367 | .016 |
| Average open Box time | .962 | 1.046 | .984 | .919 | .948 | .976 | .980 | F(2,72)=.739 | .481 |
| Look again or not | .282 | .429 | .128 | .486 | .103 | .314 | .970 | F(2,71)=1.10 | .338 |
| Satisfaction with information | 1.692 | 2.086 | 2.128 | 2.057 | 3.154 | 3.257 | .955 | F(2,71)=1.673 | .195 |
| Prefer more, less or no change | 2.051 | 2.257 | 1.974 | 2.200 | 1.744 | 2.000 | .999 | F(2,71)=.048 | .953 |
| Satisfaction with choice | 2.026 | 2.086 | 1.744 | 2.143 | 1.564 | 1.886 | .973 | F(2,71)=.976 | .382 |

s- Satisficer
m-maximizer

Table 2.5 A: Chi square fit tests for Exploratory factor analysis for 1 factor, 2 factor and 3 factors for Maximizing and satisficing subscale for Study 2

| Chi square goodness of fit | 1 factor | 2 factor | 3 factor |
|---|---|---|---|
| Adaptive Maximizing | | | |
| chi square | 213.5 | 119.8 | 101.9 |
| df | 65 | 53 | 42 |
| Adaptive Maximizing | | | |
| chi square | 137.96 | 105.2 | 87.3 |
| df | 65 | 53 | 42 |

Table 2.6: Chi square difference tests for Exploratory factor analysis for 1 factor, 2 factor and 3 factors for Maximizing and satisficing subscale for Study 2

| | chi square difference | difference in degrees of freedom | p value |
|---|---|---|---|
| Adaptive Maximizing | | | |
| 1-2 factor | 93.2 | 23 | <.00001 |
| 2-3 factor | 17.9 | 11 | .081 |
| Adaptive Satisficing | | | |
| 1-2 factor | 36.76 | 12 | 0.0002443 3 |
| 2-3 factor | 13.9 | 11 | .238 |

Table 2.7: A Factor loading pattern matrix for oblique promax rotation with Maximum Likelihood Extraction and Cronbach's Alpha if Item Deleted and total

Cronbach’s Alpha for two factor s in Adaptive maximizing Subscale for Study 2

| | Factor 1 (pre-decision) | Factor 2 (post Decision) | Cronbach's Alpha if Item Deleted | Cronbach's Alpha for the Factor |
|---|---|---|---|---|
| When I am not under time pressure, I try to look at all possible options | .827 | .100 | .726 | .792 |
| When I am faced with a very large number of choices, I still try to explore all the possibilities that are available. | .588 | .239 | .730 | |
| I never settle for second best. | .485 | .217 | .737 | |
| Even when under time pressure, I try to look at all possible options | .636 | .072 | .789 | |
| I prefer to be most accurate even when it is very exhausting | .752 | .257 | .719 | |
| Whenever I am faced with a choice, I try imagining even ones that aren’t present at the moment. | .911 | -.099 | .716 | |
| When I am not given enough options I feel unsatisfied | .645 | .398 | .742 | |
| When I am faced with an adequate number of choices, I try to explore all the possibilities that are available | .728 | .284 | .762 | |
| Even when I am using something that works, I try out other options | .556 | .195 | .724 | |
| When I am forced to make quick decision I feel very agitated | .135 | .673 | .747 | .764 |
| I regret my choice as soon as I make it even if I thought it was the best choice when I made my decision | -.222 | .616 | .719 | |
| I always reconsider my decision after making a choice | -.078 | .502 | .731 | |
| I only feel regret when I know for sure I could have made a better choice | -.106 | .481 | .731 | |
| I often change my decision at the last moment | .077 | .717 | .737 | |
| After making a choice I always feel I unsatisfied | .124 | .889 | .722 | |
| I sometimes reconsider my decision when I am not happy with my final choice | .293 | .826 | .718 | |

Table 2.8: Factor loading pattern matrix for oblique promax rotation with Maximum Likelihood Extraction and Cronbach's Alpha if Item Deleted and total Cronbach’s Alpha for two factor s in adaptive maximizing subscale Study 2

| | Factor 1 (pre-decision) | Factor 2 (post Decision) | Cronbach's Alpha if Item Deleted | Cronbach's Alpha for the Factor |
|---|---|---|---|---|
| I dislike problems that can have multiple possible answers | .616 | .198 | .081 | . .865 |
| When faced with ambiguous choices I would rather find a good enough choice than keep pondering for a longtime | .624 | .150 | .083 | |
| I am quick at deciding what I want | .754 | .279 | .084 | |
| Quick and dirty decisions are as good as slow and laborious decisions | .804 | .178 | .081 | |
| In ambiguous situations, I go with my "best guess". | .553 | .050 | .084 | |
| When I search for information I select an option based on a few, best attributes | .765 | .006 | .082 | |
| I always consider past decisions for making new decisions in similar situations | .717 | .215 | .084 | |
| When I see too many options I feel uncomfortable | .889 | -.038 | .082 | |
| **.** When searching for information some attributes are more important than others and I need to consider only the important ones | .603 | .181 | .084 | |
| Once I make a decision I don't look back | .044 | .669 | .081 | . .853 |
| I am mostly confident with my decisions | .063 | .587 | .082 | |
| After making a decision, I find that I often go back and re-evaluate my choice | .061 | .547 | .084 | |
| I don't change my decision even when better options are available | .277 | .796 | .082 | |
| When I am forced to make quick decisions I feel happy I am done | .071 | .720 | .082 | |
| I am always satisfied with my choice even when I know it is not the best one | -.094 | .604 | .082 | |
| I often change my decision at the last moment | .110 | .781 | .082 | |

Table 2 .9 :Confirmatory factor analysis to test the model fit for AISS scale for Study 3

| Goodness of fit criteria | 32 items Scale with 1 factor | 32 items Scale with 2 factors | 16 items Adaptive maximizing Scale with 1 factor | 16 items Adaptive maximizing Scale with 2 factors | 16 items Adaptive satisficing Scale with 1 factor | 16 items Adaptive satisficing Scale with 2 factors |
|---|---|---|---|---|---|---|
| S–B $\chi 2$ ($\Delta$df) | | 18.6499* (1) | | 14.6203 * (1) | | 13.541* (1) |
| CFI>0.9 | CFI=0.712 | CFI=0.798 | CFI=0.908 | CFI=0.94 | CFI=0.753 | CFI=0.916 |
| TLI>.95 | TLI=0.692 | TLI=0.784 | TLI=0.894 | TLI=0.931 | TLI=0.715 | TLI=0.885 |
| RMSEA <0.8 | RMSEA=.117 | RMSEA=.098 | RMSEA=.104 | RMSEA=.084 | RMSEA=.136 | RMSEA=.118 |
| SRMR <0.6 | SRMR=.107 | SRMR=.094 | SRMR=.048 | SRMR=.0.41 | SRMR=.083 | SRMR=.073 |

Note:

S–B $\chi 2$= Satorra–Bentler chi-square; df- degrees of freedom; CFI1-Comparative Fit Index; TLI1- Tucker Lewis Index; RMSEA-Root Mean Square Error of Approximation; AIC-Akaike Information Criterion; Adjusted-BIC-Sample size-adjusted Bayesian Information Criterion; SRMR- Standardized Root Mean Square Residual.

2.10 : Latent class analysis for classes, class probabilities, number/proportion of people in each class for Study 3

| | Classification probabilities | Class count | Class proportions |
|---|---|---|---|
| 1 | .994 | 254 | 0.348 |
| 2 | 1 | 108 | .148 |
| 3 | .983 | 152 | .208 |
| 4 | .996 | 214 | .293 |

Table 2.11: Mean, S.D and F test to show effect of LCA classes on AISS scale, situational dilemma and daily decisions

| | | adaptive satisficing | maximizing | satisficing | Adaptive maximizing | Total | F TEST | Posthoc LSD |
|---|---|---|---|---|---|---|---|---|
| AISS | Mean | 3.3039 | 4.1260 | 3.7361 | 4.5493 | 3.8822 | 127.81** | 4>2>3>1 |
| | SD | 3.1937 | 1.1220 | 2.1344 | 3.6846 | 5.8968 | | |
| Daily decisions | Mean | 3.3833 | 4.0148 | 3.5250 | 2.9225 | 3.37 | 46.28** | 2>3,1>4 |
| | SD | .80927 | .69104 | .88454 | .78413 | .875 | | |
| Situational Dilemma | Mean | 1.9998 | 2.1365 | 2.0266 | 2.0000 | 2.0262 | 112.308** | 2>3>4,1 |
| | SD | .00301 | .14078 | .09330 | .00000 | .08424 | | |

Table 2.12 Correlations among Study variables Study 3

| | AM | AS | MTS | MS | DMI | inde | avo | reg | neu | Li S | NFC |
|---|---|---|---|---|---|---|---|---|---|---|---|
| AM | **(.82)** | | | | | | | | | | |
| AS | **.71** | (.77) | | | | | | | | | |
| MTS | **.62** | **.38** | (.78) | | | | | | | | |
| MS | **.31** | **-.34** | .48 | (.59) | | | | | | | |
| DMI | **74** | **.26** | **.33** | .15 | (.76) | | | | | | |
| indecision | .54 | **-.59** | .14 | **.40** | .02 | (.93) | | | | | |
| avoidance | .19 | -.07 | .19 | **.53** | .15 | **.54** | (.72) | | | | |
| regret | .25 | **-.34** | .27 | **.48** | **.42** | **.46** | **.39** | (.94) | | | |
| neuroticism | .04 | -.01 | .12 | **.36** | .03 | .05 | .07 | .28 | (.86) | | |
| Life satisfaction | .08 | **.32** | .02 | **-.37** | -.02 | -.01 | .03 | .07 | -.13 | (.72) | |
| Need for cognition | **.27** | -.09 | .24 | .05 | .24 | .1 | .01 | .05 | -.07 | .03 | (.85) |

Bold indicates p<.05
Coefficient alpha reliabilities are provided in parentheses along the diagonal
AM=adaptive maximizing
AS=adaptive satisficing
MS= Maximizing scale
MTS= Maximizingtendency scale
DMI=decision making inventory
Life stat=life satisfaction

Table 2.13 List of attributes for pilot Study with mean ranks

| Apartment Attributes | Mean Rankings |
|---|---|
| Utilities included in rent | 7.5811 |
| Availability of gym | 24.2162 |
| Furnished/Unfurnished | 21.8378 |
| Availability of online apartment ratings | 16.4189 |
| Distance from school | 11.5405 |
| School bus availability to campus | 21.6216 |
| Parking availability | 11.2973 |
| Amount of deposit | 10.7568 |
| Cleanliness | 9.7297 |
| Age of apartment | 18.1351 |
| Allow/Not allow outside grill | 29.8514 |
| Professionalism of landlord | 14.2027 |
| distance to nearby park | 29.6081 |
| Number of bedrooms | 14.0541 |
| Area in square feet | 14.4324 |
| Neighborhood safety/Crime rate | 9.8514 |
| Laundry location | 15.2432 |
| Availability of pool | 28.7703 |
| Duration of lease (in months) | 13.6216 |
| Distance from shopping areas | 24.3919 |
| Late fee on rent | 16.5811 |
| Job opportunities near apartment | 19.3243 |

| | |
|---|---|
| Gas vs Electric appliances | 17.7297 |
| Number of bathrooms | 18.6892 |
| Other college students in area | 24.6081 |
| Pet policy/pet deposit | 25.0811 |
| Rent per month | 7.1757 |
| Real wood floors | 30.5135 |
| With or without balcony/patio | 27.3784 |
| Good lighting fixtures | 24.4459 |
| Number of electrical outlets per room | 23.0811 |
| Walk in closets | 26.9459 |
| Number of internet or cable jacks | 23.3919 |
| Availability of on call maintenance | 18.8649 |
| Quietness of neighbors/outside | 16.1351 |
| Security measures (security guards/ security cameras) | 12.3514 |
| Proximity to local attractions(Movies, bars, restaurants) | 23.5405 |

Table 2.14 : Multivariate test for effect of choice complexity, maximizing score and AISS interaction effect of choice complexity, AISS and maximizing on dependent measures combined for Study 4

| | | | | | |
|---|---|---|---|---|---|
| Effect | Wilks' Lambda | F | Hypothesis df | Error df | Sig. |
| AISS | .519 | 6.570 | 21.000 | 537.513 | .000 |
| Choice complexity | .590 | 18.561 | 7.000 | 187.000 | .000 |
| MS | .914 | 2.514 | 7.000 | 187.000 | .017 |
| AISS X choice complexity | .771 | 2.423 | 21.000 | 537.513 | .000 |
| Choice complexity x MS | .958 | 1.166 | 7.000 | 187.000 | .324 |
| AISS X choice complexity x MS | .889 | 1.066 | 21.000 | 537.513 | .381 |

Table 2.15: Main effect of Choice Complexity on each ofthe dependent measures for Study 4

| Dependent Variable | Mean Choice complexity | | Std. Error Choice complexity | | F |
|---|---|---|---|---|---|
| | 4 | 12 | 4 | 12 | |
| Average acquisition | 1.39 | .914 | .052 | .055 | 57.569* |
| Proportion of open boxes | .874 | .555 | .020 | .022 | 61.365* |
| Average open box time | 1.038 | .991 | .051 | .054 | .567 |
| Look again or not | 3.149 | 2.977 | .181 | .192 | .422 |
| Satisfaction with information | 2.807 | 2.191 | .156 | .166 | 1.446 |
| Prefer more, less or no change | 2.301 | 1.797 | .034 | .036 | 37.515* |
| Satisfaction with choice | 2.966 | 2.319 | .068 | .072 | 10.980* |

Table 2.16: Main effect of information search style on each ofthe dependent measures for Study 4

| Dependent Variable | Mean | | | | F |
|---|---|---|---|---|---|
| | satisficers | adaptive satisficers | adaptive maximizers | maximizers | |
| Average acquisition | .772 | 1.062 | 1.317 | 1.473 | 23.495* |
| Proportion of open boxes | .534 | .669 | .774 | .881 | 35.687* |
| Average open box time | 1.068 | 1.018 | .956 | 1.017 | .562 |
| Look again or not | .020 | 1.735E-018 | .115 | .307 | 10.992* |
| Satisfaction with information | 3.173 | 2.548 | 2.592 | 3.738 | 6.174* |
| Prefer more, less or no change | 1.311 | 1.988 | 2.294 | 2.601 | 45.985* |
| Satisfaction with choice | 1.985 | 2.476 | 2.524 | 3.583 | 12.093* |

Table 2.17: Main effect of maximizing tendency on each ofthe dependent measures for Study 4

| Dependent Variable | Mean | | Std. Error | | F | P value |
|---|---|---|---|---|---|---|
| | 1.00 | 2.00 | 1.00 | 2.00 | | |
| Proportion of open boxes | 1.031 | 1.240 | .059 | .047 | 7.629 | .006 |
| Average acquisition | .678 | .744 | .023 | .018 | 4.938 | .027 |
| Average open box time | 1.047 | .989 | .058 | .046 | .615 | .434 |
| Look again or not | 2.520 | 3.069 | .207 | .163 | 4.331 | .039 |
| Satisfaction with information | 2.183 | 2.814 | .179 | .141 | 7.661 | .006 |
| Prefer more, less or no change | .062 | .117 | .039 | .031 | 1.231 | .269 |
| Satisfaction with choice | 2.063 | 2.014 | .078 | .061 | .243 | .623 |

Table 2.18 : Interaction effect of adaptive information search and choice complexity on each ofthe dependent measures for Study 4

| Dependent Variable | Choice Complexity | Mean | | | | F (3,201) | P value |
|---|---|---|---|---|---|---|---|
| | | satisficers | adaptive satisficers | adaptive maximizers | maximizers | | |
| Average acquisition | 4 | .992 | 1.340 | 1.634 | 1.629 | 1.235 | .298 |
| | 12 | .553 | .784 | 1.000 | 1.317 | | |
| Proportion of open boxes | 4 | .703 | .852 | .972 | .967 | 4.091 | .008 |
| | 12 | .365 | .485 | .576 | .795 | | |
| Average open box time | 4 | 1.076 | 1.060 | .966 | 1.050 | 0.68 | .977 |
| | 12 | 1.059 | .977 | .945 | .984 | | |
| Look again or not | 4 | .040 | 3.469E-018 | .135 | .321 | 0.48 | .986 |
| | 12 | 5.551E-017 | .000 | .095 | .292 | | |
| Satisfaction with information | 4 | 2.160 | 3.095 | 2.946 | 4.393 | 11.95 | .001 |
| | 12 | 4.185 | 2.000 | 2.238 | 3.083 | | |
| Prefer more, less or no change | 4 | 1.400 | 2.476 | 2.541 | 2.786 | 4.073 | .008 |
| | 12 | 1.222 | 1.500 | 2.048 | 2.417 | | |
| Satisfaction with choice | 4 | 1.600 | 2.952 | 2.811 | 4.500 | 7.821 | .001 |
| | 12 | 2.370 | 2.000 | 2.238 | 2.667 | | |

Table 2.19: Interaction effect of maximizing and choice complexity on each ofthe dependent measures for Study 4

| Dependent Variable | Choice size | Mean | | Std. Error | | F | P value |
|---|---|---|---|---|---|---|---|
| | | S | M | S | M | | |
| Average acquisition | 4 | 1.218 | 1.521 | .079 | .067 | 1.579 | .210 |
| | 12 | .845 | .958 | .089 | .065 | | |
| Proportion of open boxes | 4 | .843 | .893 | .031 | .027 | .272 | .602 |
| | 12 | .512 | .594 | .035 | .026 | | |
| Average open box time | 4 | 1.122 | 1.021 | .077 | .066 | .333 | .564 |
| | 12 | .971 | .956 | .087 | .063 | | |
| Look again or not | 4 | 2.545 | 3.443 | .275 | .235 | 1.748 | .188 |
| | 12 | 2.495 | 2.695 | .310 | .226 | | |
| Satisfaction with information | 4 | 2.306 | 3.307 | .238 | .203 | 2.626 | .107 |
| | 12 | 2.060 | 2.321 | .268 | .196 | | |
| | 4 | .013 | .142 | .052 | .045 | 2.208 | .139 |
| | 12 | .111 | .092 | .059 | .043 | | |
| Prefer more, less or no change | 4 | 2.243 | 2.272 | .103 | .088 | .613 | .435 |
| | 12 | 1.882 | 1.756 | .116 | .085 | | |

Table 2.20: Multiple linear regressions and multiple logistic regression to analyze effect of AISS with or without controlling for MS

| Model | | Unstandardized Coefficients | | t | $R^2$ change |
|---|---|---|---|---|---|
| | | B | Std. Error | | |
| Average acquisition | No control | .276 | .044 | 6.243* | .158* |
| | Control for AISS | .099 | .052 | 1.904 | .013* |
| Proportion of open boxes | No control | .126 | .021 | 5.992* | .147 |
| | Control for AISS | .019 | .024 | .806 | .002 |
| Open box time | No control | -.036 | .036 | -1.018 | .005 |
| | Control for AISS | -.031 | .045 | -.694 | .002 |
| Satisfaction with given information | No control | .218 | .146 | 1.492 | .011 |
| | Control for AISS | .143 | .182 | .787 | .003 |
| Satisfaction with given choice | No control | .467 | .127 | 3.675* | .061* |
| | Control for AISS | .075 | .152 | .493 | .001 |
| Look for more or not | No control | .088 | .025 | .794* | .054* |
| | Control for AISS | .024 | .031 | .233* | .003 |
| Choice preference2 Less vs more | No control | -.676 | .222 | 9.271 | .104* |
| | Control for AISS | -.014 | .070 | -.197 | .001 |

Table 2.21. Multiple linear regressions and multiple logistic regression to analyze effect of MS with or without controlling for AISS

| Model | | Unstandardized Coefficients | | t/ wald | $R^2$ change |
|---|---|---|---|---|---|
| | | B | Std. Error | | |
| Average acquisition | No control | .439 | .052 | 8.477 | .257 |
| | Control for MS | .376 | .065 | 5.796* | .119* |
| Proportion of open boxes | No control | .226 | .024 | 9.497* | .302* |
| | Control for MS | .211 | .030 | 7.055 | .167* |
| Open box time | No control | -.031 | .045 | -.703 | .002 |
| | Control for MS | -.008 | .056 | -.137 | .001 |
| Satisfaction with given information | No control | .284 | .182 | 1.557* | .012 |
| | Control for MS | .174 | .230 | .759 | .003 |
| Satisfaction with given choice | No control | .892 | .151 | 5.898* | .144 |
| | Control for MS | .834 | .191 | 4.367* | .079* |
| Look for more or not | No control | -10.204 | 1.970 | Wald2 6.833* | .208 |
| | Control for MS | 1.523 | .457 | Wald 11.124* | .112* |
| Choice preference2 Less vs more | No control | -1.602 | .357 | Wald 20.070* | .338 |
| | Control for MS | .660 | .088 | Wald 7.498* | .192* |

Table 2.23 Interaction effects of AISS, MS and choice complexity

| | | B | S.E. | Wald/t | $R^2$ Change |
|---|---|---|---|---|---|
| Average Acquisition | Average acquisition | .120 | .043 | 2.794* | |
| | zmsxcomplexity | -.067 | .065 | -1.025 | .031 |
| | three-way interaction | .143 | .065 | 2.207* | |
| Proportion of open boxes | zaissxcomplexity | .116 | .053 | 2.201* | .021 |
| | zmsxcomplexity | .024 | .053 | .459 | |
| | three-way interaction | .080 | .035 | 2.291* | |
| Open box time | zaissxcomplexity | -.082 | .088 | -.925 | .014 |
| | zmsxcomplexity | .086 | .089 | .961 | |
| | three-way interaction | -.070 | .059 | -1.186 | |
| Satisfaction with given information | zaissxcomplexity | -.251 | .081 | -3.090* | .158 |
| | zmsxcomplexity | -.159 | .082 | -1.944* | |
| | three-way interaction | .066 | .054 | 1.221 | |
| Satisfaction with final choice | zaissxcomplexity | -.172 | .078 | -2.218* | .072 |
| | zmsxcomplexity | -.108 | .078 | -1.375 | |
| | three-way interaction | .039 | .051 | .767 | |
| Look for more or not | zaissxcomplexity | .258 | .360 | .514 | .008 |
| | zmsxcomplexity | -.021 | .375 | .003 | |
| | three-way interaction | .032 | .299 | .011 | |
| Choice preferences1 Less vs no change | zaissxcomplexity | .308 | .196 | 2.456 | .35 |
| | zmsxcomplexity | -.005 | .194 | .001 | |
| | three-way interaction | .023 | .131 | .030 | |
| Choice preferences1 Less vs more | zaissxcomplexity | .146 | .301 | .234 | .08 |
| | zmsxcomplexity | -.342 | .266 | 1.657 | |
| | three-way interaction | .139 | .268 | .268 | |

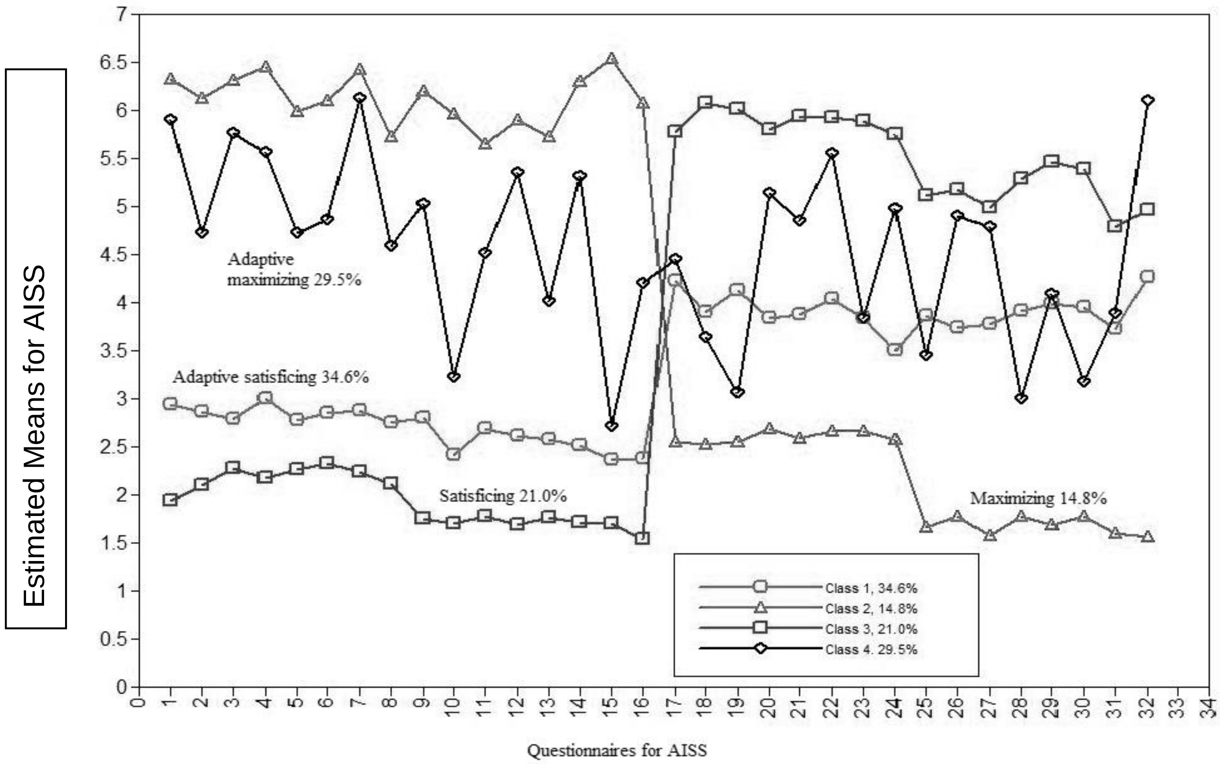


Figure 2-1 Latent Class Analysis plot show 4 different classes for adaptive information search scale

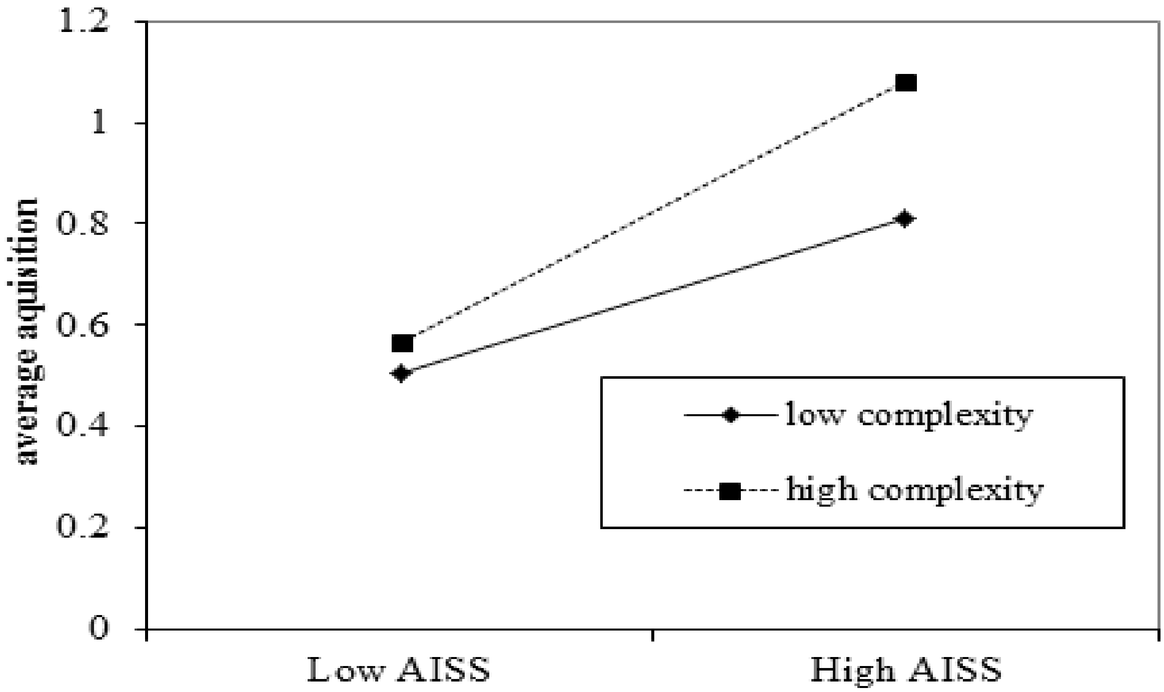


Figure 2-2 Interaction effect of AISS and choice complexity on average acquisition

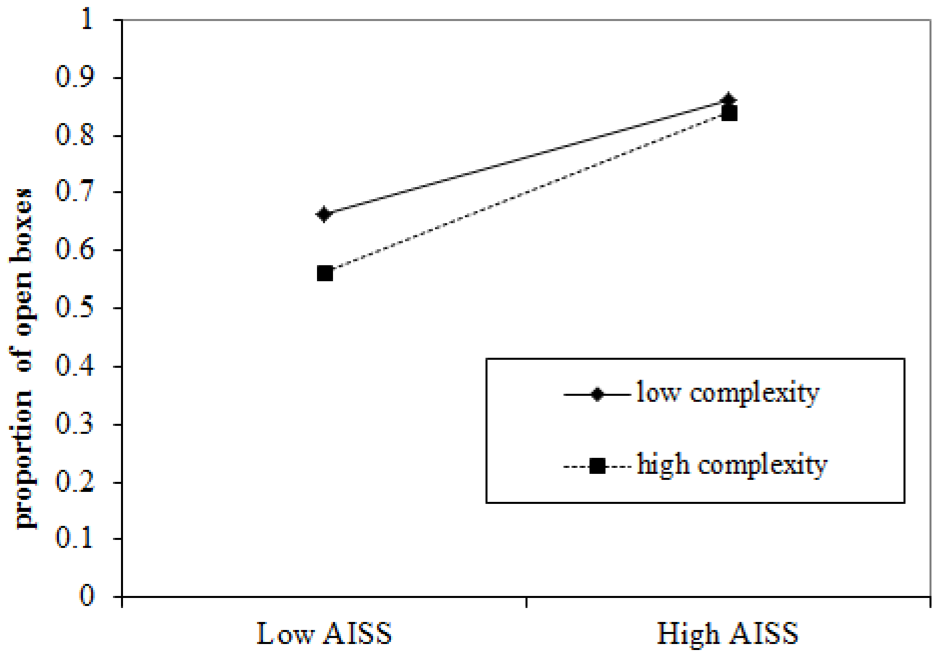


Figure 2-3 Interaction effect of AISS and choice complexity on proportion of open boxes

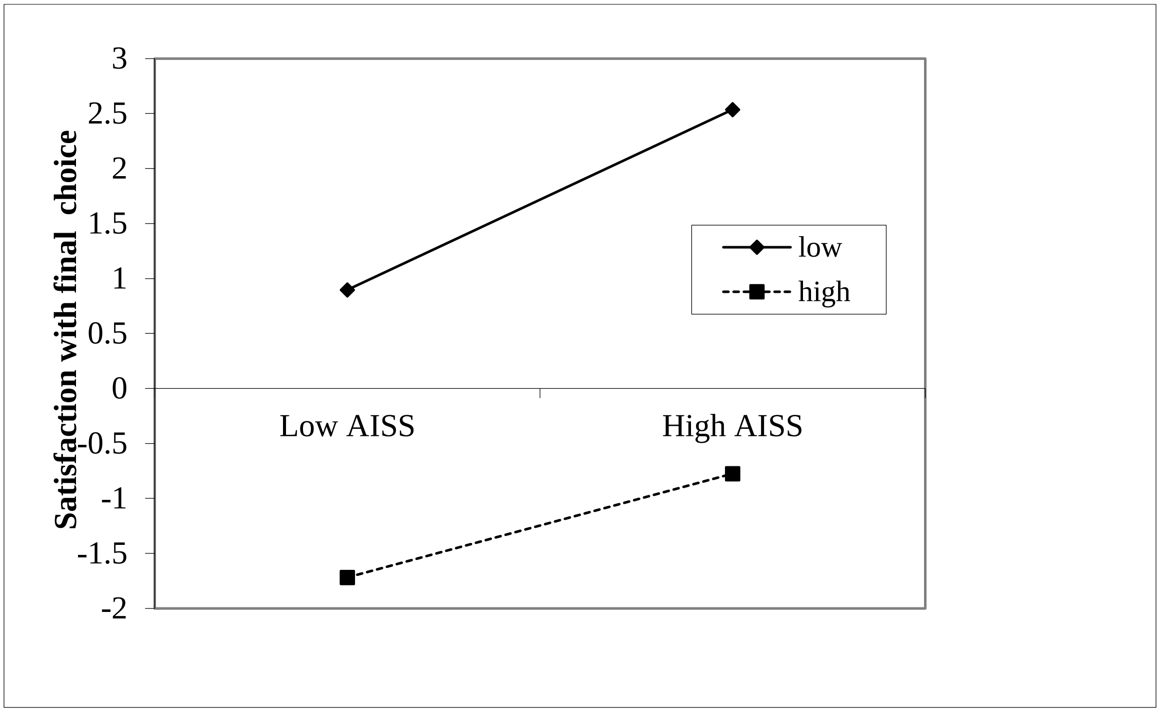


Figure 2-4 Interaction effect of AISS and choice complexity on satisfaction with final choice

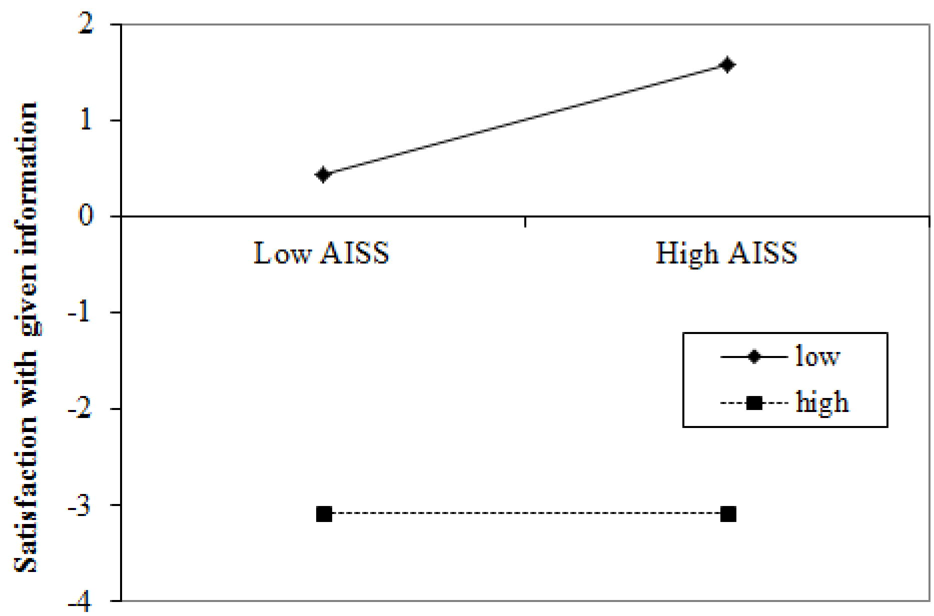


Figure 2-4 Interaction effect of AISS and choice complexity on satisfaction with given information

**Appendix B**

**Questionnaires Used in the Study**

**B.1 The Adaptive information Search Scale (Study 2)**

1. When I think I have made an adequate choice, it's only right for metro be on the lookout for better opportunities.(new)
2. When I am faced with a very large number of choices, I still try to explore all the possibilities that are available.(new)
3. When I am faced with adequate number of choices, I try to explore all the possibilities that are available (new)
4. Even when I think I have made the best choice, I am on the look for better opportunities.(new)
5. Even when under time pressure, I try to look at all possible options.(new)
6. When I am not under time pressure, I try to look at all possible options.(new)
7. I would rather do something that requires little thought than something that is sure to challenge my thinking abilities.

Whenever I’m faced with a choice, I try to imagine what all the other possibilities are, even ones that aren’t present at the moment.(MTS) .

8. I seek out the best choice there is even when it is slightly time consuming.(new)
9. I seek out the best choice there is even when it is very time consuming.(new)
10. If I make a choice and it turns out to bathe best, I feel like something of a failure if I find out if I missed any choices that were equally good.
11. I never settle for second best.(MS, MTS)
12. I only settle for second best when finding best choice is very difficult.(New)
13. I prefer to be most accurate even when it is very exhaustive.
14. I prefer to be most accurate whenever possible.
15. I value looking at all possible option over finding the most accurate answer.
16. I value accuracy over looking at all possible options.
17. Whenever I make a choice, I'm always curious about what would have happened if I had chosen differently.
18. If I make a choice and it does not turn out well, I feel like something of a failure if I find out that another choice would have turned out better.
19. I dislike problems that have multiple possible answers.
20. Once I make a decision, I don't look back.
21. After making a decision, I find that I often go back and re-evaluate my choice.
22. I don't change my decision even when better options are available
23. When faced with ambiguous choices, I would rather find a "good enough" choice than keep pondering for a longtime.
24. I often change my decision at the last moment.

25. I am quick at deciding what I want.
26. When I have made a decision, I feel relieved.
27. When I am confronted with a problem, I'm dying to reach a solution very quickly
28. My decisions usually result from using the "quick and easy" approach
29. My decisions usually result from using the "slow but sure" approach.
30. In ambiguous situations, I go with my "best guess."
31. The only way to make a good decision is to consider all the possible options.
32. My best decisions are those for which I've carefully considered all the options.
33. Quick and dirty decisions are as good as slow and laborious decisions.
34. When I know all possible information cannot be made available, I make a choice with what is available
35. When I know all possible information cannot be made available, I still look for information in other places before I make a decision.
36. When I search for information, I select options based on a few "best" attributes.
37. When I search for information, I look for all attributes of one alternative and then move onto the next.
38. When I search for information, I make sure that I look for all attributes and alternatives but not in any particular order.
39. When searching for information, all attributes are equally important and need to be considered equally.
40. When searching for information, some attributes are more important than others. We need to consider all of them but give more weight to the most important ones.

41. When searching for information, some attributes are more important than others and we need to consider only important ones.
42. I don’t like having to settle for “good enough.” (MTS)
43. I always consider past decisions when making new decision in all situations.
44. I always start from scratch and look at all information when making a decision even when I have faced similar situation in the past.
45. When forced to make a quick decision, I use information that readily comes to mind to make a choice.
46. I only get upset with my choice when they don’t turn out well.
47. Even when I am overwhelmed with choice I still keep looking.
48. When I see too many options I feel uncomfortable.
49. When overwhelmed with too much choice I quickly choose anything that seems right.
50. I am always happy with my choice, even though they are not the best.
51. When I am not given enough options I feel unsatisfied
52. I find simple strategies for selection very gratifying.
53. I don't feel satisfied until I use a complex selection strategy
54. I am uncomfortable making decisions before I know all of my options.(MTS)
55. As long as a few good options are available I am content.
56. I am never happy with my decisions.
57. After making a choice I always feel I could have made a better decision.
58. I am always satisfied with my choice even when I know it is not the best one.

59. I regret my choice as soon as I make it even if I thought it was the best choice when I made the decision.
60. I only regret when I know for sure that I could have made a better choice.
61. When I am forced to make a quick decision I feel very agitated.
62. When I am forced to make quick decisions I feel happy when I am done.
63. Whenever I am faced with a choice, I try to explore all the possibilities that are available.
64. I will wait for the best option, no matter how long it takes.(MTS)

**B.2 Maximizing Scale**

1) When I watch, I channel surf, often scanning through the available options even while attempting to watch one program.
2) When I am in the car listening to the radio, I often check other stations to see if something better is playing, even if I am relatively satisfied with what I am listening to.
3) I treat relationships like clothing: I expect to try on a lot before finding the perfect fit.
4) No matter how satisfied I am with my job, it's only right for metro be on the lookout for better opportunities.
5) Whenever I'm faced with a choice, I try to imagine what all the other possibilities are, even ones that aren't present at the moment
6) I often find it difficult to shop for a gift for a friend.
7) Renting videos is really difficult. I'm always struggling to pick the best one.
8) When shopping, I have hard time finding clothing that I really love.

9) I'm a big fan of lists that attempt to rank things (the best movies, the best singers, the best athletes, the best novels, etc.).

10) I find that writing is very difficult, even if it's just writing a letter to a friend, because it's so hardtop word things just right. I often do several drafts of even simple things

11) No matter what I do, I have the highest standards for myself.

12) I never settle for second best.

13) I often fantasize about living in ways that are quite different from my actual life.

### B.3 Social Dilemma Items

Please read each ofthe following scenarios and the corresponding behaviors. to clearly visualize each scenario as you read it.then, indicate which behavior you would be MOST Likely do

Response option (i.e., a, b, or c).

1. Imagine you are at the car dealership and you have found a car that you really want at the right price, however they have only one color available. There are a few bestselling color options available at another dealership but you will have to drive at the end of the town.  Alternatively, you could travel to a dealership located in the neighboring state that carries all the possible color selections.

Which behavior are you most likely to do?

(a) You will buy the car at the current dealership anyway.

(b) You will get the dealer at the other end of town to look at the bestselling colors.

(c) You will make aristo <u>another</u> the neighboring state to look at all possible color options

2. You got the mall to shop for clothes because you have a formal event coming up this weekend. You walk into a store and quickly find something that seems good enough. You try it on, and it fits well. The price also seems reasonable and affordable.

(a) You quickly buy the clothes you like and go home.

(b) You keep the clothing you like in hand and search for few more options to see if you get anything better

(c) You check out as many stores as possible until it is time to go home to make sure you get the best dress for the price

3. You are currently working. You are very satisfied with your job; it is the best job you have had in years. A recruiter contacts you saying he might have a similar job with better pay.

(a) You stay in your current job because you like it.

(b) You don't actively look for other jobs, but you make an appointment to check out the job your recruiter offered.

(c) You actively start look for other jobs and contact other recruiters because you feel that there must be a better ones out there.

4. You have to find housing for next year pretty soon. You are living in an apartment that you like; however, there is another apartment that you like even more and you really want to live there. Although there is a good chance that the apartment will be available, you

won’t know for sure until after the deadline for signing the lease for your current apartment.

(a) You sign the lease for your current apartment because you don’t want to risk moving for no good reason.

(b) You wait until closet the deadline to reserve the new apartment and look for similar apartments even though you might not get any of them.

(c) You wait little past deadline and try to find other housing options that are available in case if you find something even better for cheap.

5. You have decided to apply for graduate school. You apply to 7 programs that you think are good programs. You get an offer from 3 of your top 5 choices including your number 2 choices. However, your best choice school that accepted you may not award you funding if you don’t provide an answer soon.

(a) You accept your number 2 choice right away; it was almost as good as number 1 anyways

(b) You wait a little bit to hear back from other 2 schools of your top 5 choices and evaluate your current options

(c) You wait until you find out about all the programs that you haven’t heard from yet.

6. You really wanted a Flat screen LED TV. On Christmas with cash gifts you finally go buy a very nice flat screentVthat you really like from a store. However after you go home you find outthe sametV is available for a bit cheaper price from an online website but you will have to wait few weeks.

a) You keep your currenttV and feel satisfied

b) You return your currenttV and orderthe one online and wait.

c) You returnthetV and start looking at other stores and online websiteto make surethere are no other options availablethat are even cheaper or better.

7. You wantto get a camera with very good zoom. You got a store you see different brands of cameras with lot of features some of them more important than others.

a) You buy the camera with best zoom in your price range

b) You look at all other features but give more weight to the ones that are more important

c) You look at all the features and try to see if there is a camera that is has all the best features in it